Raising Bond Capital in Segmented Markets

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Abstract

The cost of bond capital that firms face is determined at issuance, and often exceeds yields trading in secondary bond markets. I find that the difference between yields at issuance and in secondary markets, the "issuance premium", spikes in bad times, increasing firms' costs of capital. This suggests that the economics of the relatively understudied primary bond markets – where firms sell new bonds via underwriters to investors – are important for understanding firms' costs of capital and access to credit over the cycle. Leveraging new data on bond issuance, I estimate a model of primary markets that explains the issuance premium and its impact on bond issuance volume. Using high-frequency variation in bond supply as an instrument, I find that short-term investors are more sensitive to issuance premiums than long-term investors. As issuance premiums rise in bad times, the share of short-term investors endogenously increases, supporting bond volumes. The composition of primary market investors therefore directly affects the transmission of shocks to firms' costs of capital and bond issuance volume, as well as the price impacts of corporate bond purchase policies.

Keywords: Corporate bonds, securities issuance, unconventional monetary policy
JEL codes: G23, E44, G32, E52

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1 Introduction

Firms raise over $1 trillion in corporate bonds every year.[1] The cost of bond capital to firms is determined in the primary market – where firms sell new bonds via underwriters to investors – and often exceeds yields traded in secondary markets. The difference in primary and secondary market yields, the "issuance premium", rises in market downturns, amplifying the countercyclical pattern of secondary market credit spreads (over risk-free rates) documented by Gilchrist and Zakrajšek (2012). During the COVID-19 crisis, average issuance premiums went from 8 to 30 basis points; during the 2008-2009 financial crisis, they reached 55 basis points. Such fluctuations in external financing costs can have material impacts on firms' real activities.[2]

In this paper, I quantify how negative demand shocks in primary markets affect firm borrowing. I start with the observation that primary and secondary markets are segmented. Secondary markets exclude firms from participating, while primary markets are run by broker-dealers who are known to favor some investors and exclude others.[3] Indeed, I document facts consistent with investor segmentation: primary investors are larger than their counterparts in secondary markets, and on average 20% of them "flip" the bond within days, causing a sharp spike in trading post-issuance, while the remainder rarely trade.

Because this segmentation leads to limited investor capacity to absorb shocks, shifts in supply and demand in primary markets can impact firms' costs of capital (Duffie (2010)). To quantify how much, I estimate an equilibrium model of primary markets using a new industry dataset and high-frequency identification. I show that on the supply side, firms' lower sensitivity to prices in bad times exacerbates the impact of negative demand shocks on issuance premiums. On the demand side, higher issuance premiums attract a larger proportion of more price-elastic short-term investors who "flip" the bond, dampening the spike in issuance premiums and accommodating more issuance. Firms can thus access more bond capital in bad times due to higher issuance premiums attracting more short-term investors, relative to a counterfactual with only buy and hold investors. The preferences of primary market participants therefore directly affect the transmission of shocks to firms' costs of capital and access to credit.

[1] Source: SIFMA Capital Markets Fact Book, 2021.
[2] See *inter alia* Bolton et al. (2013) and Campello et al. (2011).
[3] See *inter alia* Benveniste and Spindt (1989) and Cornelli and Goldreich (2001).

An illustrative example of primary market dynamics is the spring 2020 bond issuance by the luxury retailer Nordstrom. Amidst the closing of all stores due to the COVID-19 pandemic, the company sought to raise $600 million of bonds on April 8 in order to shore up cash reserves. The bond was issued at 8.75% – their highest bond yield since prior to the 2008 financial crisis – and received $6 billion in investor orders. Short-term investors purchased 40% of the bond, double the average share. Within the first day, the credit spread dropped over 100 basis points once trading in secondary markets began, suggesting that underwriters had "left money on the table" by pricing the bond at a higher yield (or lower price) than market clearing. The Nordstrom example aligns with facts I document about primary markets. Large order books along with a first day drop in credit spreads indicate restricted access to primary markets, consistent with market segmentation. Moreover, short-term investors generally participate more during downturns, when issuance premiums are higher.

Motivated by these facts, I develop and estimate an equilibrium model of corporate bond issuance. The model incorporates demand from two types of primary market investors (short-term and long-term), supply from issuing firms, and underwriters who split surplus between firms and investors via pricing (credit spreads). I allow primary market investors to have different preferences over the two components of new issue credit spread: the issuance premium and the secondary market credit spread. I then estimate the demand elasticities of the two types of primary market investors and firm supply elasticities.[4] Importantly, the model produces simulated counterfactual equilibria which allow me to quantify how changes in firm fundamentals, investor composition, and underwriter favoritism impact bond prices and volumes.

New micro-data on corporate bond issuance from Credit Flow Research (CFR) and Informa Global Markets (IGM) provides high-frequency variation in bond-level issuance information that allows me to identify supply-side parameters. Specifically, this dataset includes order books at issuance and changes in credit spreads and bond sizes throughout the issuance process. I combine this with a comprehensive dataset of trading, holdings, bond, and firm characteristics from the Enhanced Trade Reporting and Compliance Engine (TRACE), Thomson Reuters eMAXX, the National Association of Insurance Commissioners (NAIC), Mergent FISD, and Compustat. The

[4] To be precise, I estimate semi-elasticities with respect to credit spread: that is, the percentage change in quantities given a level change in credit spreads. For ease of exposition, I will use the term "elasticities".

combined sample for the primary estimation is from July 2010 to June 2020.

To estimate the supply side, I exploit within-day variation in proposed issuance prices and quantities for the same bond. Within the issuance day, during which firm fundamentals are presumably constant, firms adjust quantity supplied upwards when credit spreads are lower than expected. By observing multiple price–quantity pairs from the same day, I can pin down the firm's supply elasticity based on within-bond variation. I find that on average, firms respond to a 10 basis point increase in credit spreads by decreasing issuance by 2%; during the global financial crisis (GFC), when they are more desperate for cash, they decrease issuance by half as much.[5]

Next, I estimate how investors respond to credit spreads. I take as a primitive of the model that investors are far from perfectly elastic, owing to realistic frictions such as slow-moving capital and heterogeneous institutional needs (Duffie (2010), Koijen and Yogo (2019), Gabaix and Koijen (2020), Becker and Ivashina (2015)). Indeed, the data confirms an upward-sloping demand curve for primary market bond investors: credit spreads rise when other firms issue more bonds on the same day – a positive supply shock. The same-day issuance volume of comparable securities thus becomes a supply shifter in corporate bond issuance markets that helps identify demand elasticities. While low-frequency shifts in supply could correlate with firm and macro fundamentals as firms may endogenously choose a time window (e.g., which week) to issue bonds, the specific *day* of the week is quasi-random with respect to unobserved firm characteristics when absorbing week fixed effects. The resulting estimates show that a one-basis-point increase in issuance premiums corresponds to a 7% increase in short-term investor demand, but only a 3% increase in long-term investor demand.

I compare primary market investor demand with secondary market investor demand to demonstrate the difference between these two sets of investors. I estimate secondary market demand elasticities using cross-sectional variation in institutional holdings data, following Koijen and Yogo (2019) and Bretscher et al. (2020), exploiting the investment universe of other funds as an exogenous price shifter. However, I deviate from the security-level instrument of these two papers by defining each investor's investment universe using *classes* of bonds, which are defined as bonds of the same tenor and credit rating, issued by firms in the same industry. I do this because greater demand for bonds at the investment class level generates a greater exogenous component of demand. I find

[5]In principle, firms can substitute to bank lending (Darmouni and Siani (2020)) or, increasingly, shadow banks (Buchak et al. (2018)).

that for a one-basis-point increase in credit spreads, secondary market investors increase holdings by 0.1%. The comparison of elasticities is further evidence that primary and secondary market investors are distinct groups with different preferences.

Because new bonds often attract higher quantity demanded than quantity supplied, and demand is known to be rationed,[6] the usual equilibrium notion of demand equals supply is insufficient. Thus, to close the model, I introduce underwriters who select an equilibrium credit spread that splits surplus between firms and investors, subject to market clearing. My estimation reveals that underwriters systematically favor investors, contributing to issuance premiums being positive on average. This is consistent with underwriter market power, which arises from high barriers to entry in the underwriting business.[7] These barriers have been documented as search costs and relationship-building for investors[8] , and certification costs and relationship-building for firms.[9]

I use the model and parameter estimates to simulate counterfactual equilibria that inform the drivers and effects of issuance premiums and volume changes across the cycle. I find that changes in firms' willingness to pay drive a significant portion of the cyclicality of issuance premiums, but investor participation and underwriter behavior explain the magnitudes. Investor heterogeneity plays an important role: without short-term investors endogenously entering when issuance premiums are high, the countercyclicality of issuance premiums would be over 48% more pronounced. Reductions in investor demand in bad times contribute 20% of the magnitude of the cyclicality, while underwriters' favoring of investors contributes another 29%.

To explore investor heterogeneity further, I simulate counterfactual equilibria in which (1) firms face a cash shortfall and demand more capital, and (2) investors face a range of fund outflows. As firms increase their willingness to pay for capital and investors retrench, issuance premiums rise and the composition of investors in primary markets endogenously shifts towards short-term investors. This shift leads to smaller drops in overall issuance relative to a counterfactual with no short-term investors. The phenomenon can be seen in the Nordstrom example, where large issuance premiums

[6]See *inter alia* Benveniste and Spindt (1989), Aggarwal et al. (2002), Nikolova et al. (2020), and Loughran and Ritter (2002).

[7]Moreover, the syndicate nature of underwriting could encourage collusion even if there were low barriers to entry, as broker-dealers could credibly punish any undercutting underwriter by refusing to join its syndicate; see Hatfield et al. (2020).

[8]See Duffie et al. (2005) and Henderson and Tookes (2012) for search costs, and Hendershott et al. (2020) for relationships in dealer networks.

[9]See Rajan (1992), Yasuda (2007), and Duarte-Silva (2010). In the equity issuance literature, underwriters may also favor investors to gain valuable pricing information (Benveniste and Spindt (1989)).

increased both the share of short-term investors and the quantity demanded. On the other hand, in normal times, the presence of short-term investors increases average issuance premiums by 4 basis points ($2.1 million on the median bond) relative to a counterfactual economy with only buy-and-hold investors. The dark side of an increase in short-term investors is an increase in issuance premiums on average, while the bright side is that an endogenous shift towards more short-term investors in bad times helps primary markets absorb large supply shocks.

Finally, I quantify the price impact from large exogenous bond purchases in secondary markets versus primary markets, allowing firms to endogenously respond to changes in issuance costs but holding fundamentals fixed. I find that a $6.5 million purchase of a median bond in secondary markets, where investors are relatively inelastic, leads to a drop of nearly 60 basis points in new issue credit spreads and just under $6.5 million increase in issuance volumes. However, a purchase of the same size in primary markets, where investors are quite elastic over issuance premiums, has a negligible impact on issuance volumes. These findings could inform the design of Federal Reserve corporate bond purchase programs, such as the Corporate Credit Facilities of spring 2020. My model suggests that secondary market intervention would have a larger effect on new issuance prices and volumes, owing to the relative elasticities and higher share of short-term participants in bad times.

Contributions to the literature

This paper primarily contributes to three strands of literature. First, I add to the body of work on the role of institutions in financial markets by taking the firm's perspective. While models of corporate debt typically abstract away from changes in issuance costs (Leland and Toft (1996), He and Milbradt (2014)), my paper quantifies how bond issuance prices and volumes may vary across the cycle beyond secondary market fluctuations (Gilchrist and Zakrajšek (2012)), due to institutional frictions in primary markets. Constraints on participation in primary markets mean firms' costs of capital are subject to supply and demand shocks; this is related to the concept of slow-moving capital (Duffie (2010), Greenwood et al. (2018)). Firms' costs of capital are therefore vulnerable to the supply constraints of a smaller set of investors, exacerbating the effects of limited risk-bearing capacity on asset prices (Gilchrist and Zakrajšek (2012), He and Krishnamurthy (2013), Manconi et al. (2012), Adrian et al. (2017), Adrian and Shin (2014)). Moreover, investor heterogeneity can arise from different funding structures or investment strategies (Chodorow-Reich et al. (2021), Greenwood and Vayanos (2014), Greenwood and Vayanos (2010), Vayanos and Vila (2021), Aragon and Strahan (2012)); I find this heterogeneity plays an important role in primary markets.

As institutional frictions lead to inelastic investors, recent papers have developed tools to estimate investor demand systems for securities (Koijen and Yogo (2019), Gabaix and Koijen (2020), Bretscher et al. (2020)). I build on this work by estimating investor demand while endogenizing firm supply of corporate bonds. Moreover, I quantify the effects of secular shifts in investor composition (Li and Yu (2021)) on firms' costs of capital. My estimation of demand elasticities for different investor types contributes to the literature assessing central bank policies, particularly policies regarding corporate bond purchases (Falato et al. (2020), Gilchrist et al. (2020), Flanagan and Purnanandam (2020), Boyarchenko et al. (2020), Halling et al. (2020)).

Second, I contribute to a vast literature on securities issuance in both bonds and equities. My paper relates to papers on corporate bond underpricing, including Cai et al. (2007), Goldstein and Hotchkiss (2007), Nikolova et al. (2020), Goldstein et al. (2019), and Nagler and Ottonello (2020) (see Cai et al. (2007) for a survey), by documenting the countercylical pattern of issuance premiums and quantifying the effects of investor heterogeneity and underwriter agency.[10] In the literature on equity underwriting and underpricing (see Ljungqvist (2007) for a survey), the dominant explanation for underpricing is information asymmetry. Corporate bonds are less information-sensitive than equities, for three reasons. First, information asymmetries between firms and investors (Myers and Majluf (1984)) are limited, because many investors are repeat investors (Zhu (2021)), and because bond outcomes lie within a narrow range, given low default rates.[11] Second, information asymmetries between underwriters and investors (Benveniste and Spindt (1989), Cornelli and Goldreich (2003), Booth and Smith (1986)) are mitigated by frequent bond issuance, which provides pricing benchmarks: in 2019, for example, there were 151 equity IPOs in the U.S. and 2,097 corporate bond offerings (SIFMA 2020). Finally, while underpricing may arise from information asymmetry among investors (Rock (1986)), particularly between institutions and the retail buyers who hold 32% of U.S. equities (Green (2007)), less than 7% of corporate bonds are held by retail investors.[12]

[10]Moreover, U.S. Treasury bonds are known to have an on-the-run liquidity premium (Krishnamurthy (2002), Vayanos and Weill (2008)); the issuance premium I document is in the opposite direction.

[11]Corporate bonds historically have low default rates: since 1981, default rates for investment-grade corporate bonds have remained well below 1%, peaking at 0.42% in 2002 and 2008, in the wakes of the dotcom crisis and the GFC, respectively. Source: "Default, Transition, and Recovery: 2019 Annual Global Corporate Default and Rating Transition Study", S&P Global, April 29, 2020.

[12]Source: Federal Reserve Flow of Funds.

The primary non-information story for equity underpricing involves agency issues between underwriters and firms (Ritter and Welch (2002), Jenkinson et al. (2018), Loughran and Ritter (2002)). This also affects bond underwriting: agency costs in securities underwriting for bonds are documented in Flanagan et al. (2019) and Nikolova et al. (2020). I contribute to this literature, as well as the literature that estimates structural methods to study the effects of imperfect competition in financial markets (Robles-Garcia (2019), Eisenschmidt et al. (2020), Wang et al. (2020), Xiao (2020), Drechsler et al. (2017), Scharfstein and Sunderam (2016)), by explicitly modeling underwriters' surplus split between firms and investors and quantifying the effect on fluctuations in costs of capital.

Third, my findings complement a broad literature that documents frictions in secondary markets for corporate bonds by relating them to primary markets. Corporate bonds are traded over-the-counter and are subject to search costs, inventory holding costs, and heterogeneous bargaining power (Duffie et al. (2005), Duffie et al. (2007), Lagos and Rocheteau (2009), Gavazza (2016)). These transaction costs decrease liquidity and increase expected returns (Amihud and Mendelson (1986)). The literature on this subject would suggest higher transaction costs in times of greater market volatility, when bonds are overall more illiquid (Bao et al. (2011)), since dealers are less willing to take riskier and more illiquid bonds into inventory (Goldstein and Hotchkiss (2020)). Moreover, because of post-crisis shifts in regulation, liquidity provision in corporate bond markets has become costlier (Dick-Nielsen and Rossi (2019)) and has moved away from bank-affiliated dealer capital (Duffie (2012), Bessembinder et al. (2018), Bao et al. (2018), Choi and Huh (2019)), increasing the importance of non-bank dealers such as primary market investors. Finally, dealers have relationship networks (Hendershott et al. (2020)) and exercise market power to benefit more active investors and to investors with whom they have relationships (O'Hara et al. (2018), Di Maggio et al. (2017)), just as underwriters do in the primary market setting.

The rest of the paper is organized as follows. Section 2 describes the data and institutional background of corporate bond issuance. Section 3 describes empirical facts characterizing the corporate bond market. Section 4 introduces the model, and Section 5 presents the estimation strategy and the parameter estimates. Section 6 discusses results and counterfactual analyses. Section 7 concludes.

2 Data and background

2.1 Data

For the empirical analysis, I compile a novel and comprehensive dataset on corporate bond issuance. New data comes from Informa Global Markets (IGM) and Credit Flow Research (CFR). These industry data providers survey broker-dealers daily to collect bond issuance information including order book size, the range of credit spreads announced during the issuance process, and adjustments to bond issuance size and credit spreads. I merge this data with Mergent FISD to get bond-level data including ratings, tenor, maturity, and seniority; with NAIC bond-investor purchase data to identify insurance investors; and with Enhanced TRACE data to track trading in the first days post-issuance. I further merge with holdings data from Thomson Reuters eMaxx to estimate secondary market demand. I include only fund-years that hold at least 20 unique bonds. For the bonds in my sample, the eMAXX data covers about 50% of holdings at quarter end.

Using the Enhanced TRACE data, I compute issuance premiums as the difference between the new issuance credit spread and the trade-weighted average of sell-side trades completed by the end of the first day post-issuance. I omit extreme values with changes of greater than 300 basis points. The metric nets out changes in U.S. Treasury yields and other market conditions. Because bonds are issued close to par, this measure represents firms' incremental annual cost of capital. On a yield basis, issuance premiums are 8 basis points on average.[13] For robustness, I compute several alternative metrics: the same computation but over the first 3- and 7- days, the underwriters' view of issuance premiums collected by IGM/CFR, and a price-based first day excess return as proposed by Cai et al. (2007). See Appendix A.4 for details.

I use the order book variable from IGM/CFR as the metric for primary market investor demand. This measures the total quantity demanded by all investors at the new issue yield for each bond. For the share of short-term investors in each bond issue, I compute the ratio of total sell orders in the secondary market in the first week following issuance (as reported by Enhanced TRACE) to the size of the bond (as reported by FISD). The share of long-term investors is one minus the

[13] While I use a yield-based metric in my analysis, I can more easily compare to benchmarks in the literature by computing a price-based analogue. The first-day excess price-based return relative to the Bloomberg Aggregate Bond Index as proposed in Cai et al. (2007) averages 52 basis points in my sample, significantly larger than the average bid-ask spread of 36 basis points.

short-term share.

I merge issuer-level data with Compustat to get firm characteristics, and with Markit credit default swap (CDS) quotes to compute probabilities of default. I estimate each firm's time-varying probability of default from the market spread of its CDS as per Hull (2012).[14] I collect bid–ask spreads for each bond at the monthly level from WRDS Bond Returns data. Finally, I collect historical U.S. Treasury bond yields and TED spreads (the difference between the 3-month LIBOR and the U.S. Treasury bill yield) from the St. Louis Federal Reserve and historical values of the Chicago Fed National Activity Index (CFNAI) from the Chicago Federal Reserve.

Included in the estimation are bonds that are underwritten publicly by broker-dealers and thus are included in the IGM/CFR data. These bonds tend to be larger and issued by higher-rated firms. For my primary estimation analysis, I have 4,013 US dollar corporate bonds issued by 508 non-financial, non-utility firms. See Table 8 for summary statistics of the full sample of FISD bonds (non-convertible, non-financial USD bonds of at least $100 million in size at issuance) and issuers, versus the sample available for estimation.

2.2 Background: corporate bond underwriting process

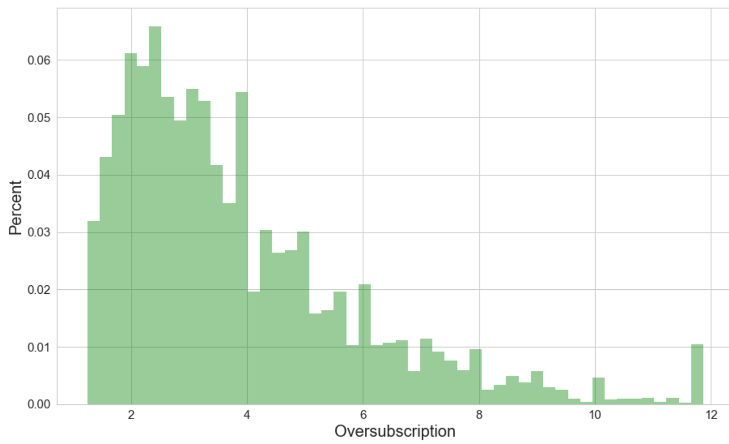
Corporate bonds are priced as a credit spread to the risk-free rate, where the risk-free rate is that of the on-the-run U.S. Treasury bond whose duration matches the duration of the bond. A group of broker-dealers leading the underwriting process conducts a price discovery process over the span of one day. In each of four rounds, the underwriters announce a potential credit spread at which the new bond could be priced, and observe the quantity demanded from investors at that credit spread. While these quantities are not transacted, investors have an incentive to report true demand because issuance is a repeated game. Once the final credit spread is set, the underwriters allocate bonds to investors. Bonds begin trading in the secondary market almost immediately following issuance.

Underwriters have the final say in the new issuance credit spread. At this final credit spread, order books as reported to IGM/CFR typically exceed the bond volume supplied by the firm. This leads to oversubscription (where the ratio of quantity demanded to quantity supplied is greater than one). Figure 1 shows the magnitude of oversubscription for newly issued bonds in my sample. As

[14] See Appendix for how I compute probability of default. I am only able to match 20% of firms with CDS, which issued 40% of the bonds in my sample. Thank you to Lira Mota for help with this merge.

can be seen in the histogram, order books are regularly over 2–3 times oversubscribed. This suggests that issuance credit spreads are commonly set above a competitive equilibrium, where supply would equal demand.

Figure 1: Distribution of oversubscription ratio



Source: Credit Flow Research and Informa Global Markets
Note: Histogram of oversubscription ratios for bonds issued 2010–2020. Oversubscription is computed as the ratio of quantity demanded to quantity supplied at the final issuance price.

Indeed, I find suggestive evidence that broker dealers are subject to agency issues in underwriting bonds when they do not internalize the costs of capital. Specifically, underwriters have smaller order books when they are both the underwriter and the issuer versus when they are underwriting a comparable bond for a different issuer (see Figure 10). I interpret this as the underwriter using discretion in setting credit spreads higher than competitive equilibrium (where order books would equal quantity supplied) in order to extract rents from issuers to give to investors.[15] When this practice is more costly because the underwriter is itself the issuer, the underwriter sets a credit spread closer to the market credit spread. This is consistent with papers that show evidence that broker-dealers have discretion in underwriting (Nikolova et al. (2020), Benveniste and Spindt (1989)). I will come back to this institutional detail when modeling the underwriter's problem.

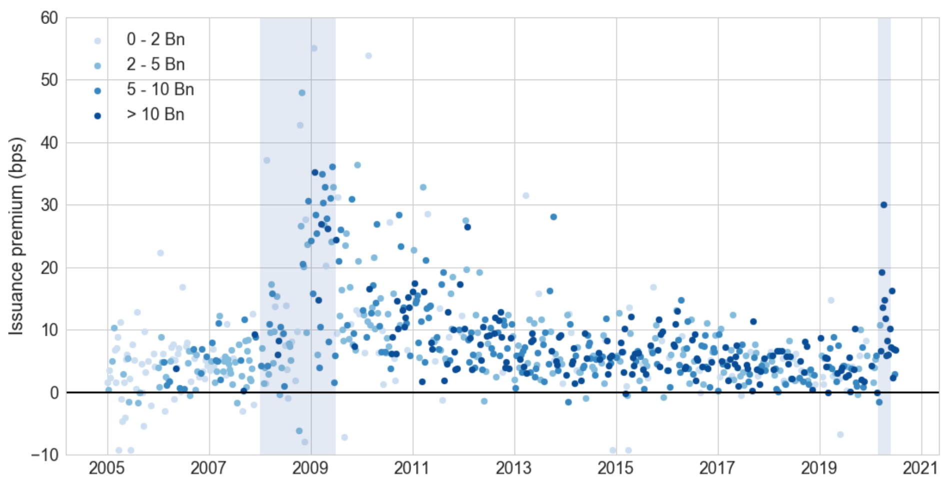
[15] An alternative story is that underwriters have more information about self-led bond issuances; I check if this is the case by comparing a proxy for price uncertainty, the relative range of credit spreads announced throughout the span of a bond issuance, for self-led versus comparable deals in Table 9. I find no significant difference in price uncertainty between self-led and comparable deals.

3 Stylized facts

In this section, I present stylized facts about the primary market for corporate bonds. First, I describe the motivating fact that issuance premiums are countercyclical. Next, I discuss three features of primary market investors: the difference in types of investors in the two markets, primary market investor behavior, and cyclical variation in this investor behavior. These facts, taken together, suggest that primary markets are segmented from secondary markets and are thus subject to shifts in supply and demand, given limited investor capacity to absorb shocks (Duffie (2010)).

3.1 Issuance premiums rise in bad times

Figure 2: First-day credit spread changes



Source: Enhanced TRACE and Mergent FISD.
Note: I plot the time series of weekly averages in issuance premium for newly-issued bonds. The issuance premium is defined as the credit spread difference, in basis points, between new issue credit spread and the volume-weighted average credit spread on sell trades reported in TRACE completed by end of the first day following issuance. A positive value indicates the bond was issued at a higher yield than post-market trading. Shaded regions are January 2008 to June 2009 and March–May 2020. Darker dots indicate weeks with greater issuance volumes.

I find that issuance premiums are countercyclical. The time-series plot in Figure 2 shows that during the GFC of 2008 and the COVID-19 crisis of 2020, there was a spike in weekly average issuance premiums. Moreover, the distribution of issuance premiums is similar within each ratings category for investment-grade issuers, as seen in Figure 11, suggesting that uncertainty around bond value (Beatty and Ritter (1986), Rock (1986)), which correlates with credit rating, is unlikely to be the only driver.

To more formally test the impact of issuer characteristics on issuance premiums, I regress the issuance premium on a proxy for economic activity, the Chicago Fed National Activity Index (CF-NAI).[16] The model is as follows:

$$IssPrem_{ubft} = \beta EconActivity_t + X_{bft}\gamma + \epsilon_{ubft}, \tag{1}$$

where b indicates bond, f is for each firm, u is for underwriter, and t is for day. See Table 1 for the results. The first column is an OLS regression of issuance premium on the CFNAI index, controlling for issuer credit rating, bond size, and bond tenor. The coefficient indicates a one standard deviation deterioration in macroeconomic conditions corresponds to one basis point increase in issuance premiums, even when accounting for bond characteristics and credit rating. This represents 12% of the magnitude of fluctuations in the Gilchrist-Zakrajšek (GZ) credit spread as measured in Gilchrist and Zakrajšek (2012), estimated over the same sample period in the last column.[17] In the second column, I add issuer characteristics – prior quarter leverage, cash to assets, and profitability – as issuer quality is known to vary across the credit cycle (Greenwood and Hanson (2013)). Even after absorbing time-series variation in firm fundamentals, the coefficient does not change significantly.

Next, I test how much issuance premiums can be explained by an increase in information asymmetry in bad times. As a proxy for information asymmetry between underwriters and investors (Benveniste and Spindt (1989)), I use the range of credit spreads provided for each bond issuance as a percentage of the final credit spread. The wider the range of credit spreads, the greater the ex-ante uncertainty of the price. I also include underwriter fixed effects to absorb any time-invariant cross-sectional variation in underwriter sophistication. I find that the countercyclical pattern persists. Alternatively, firms may have more information than investors and thus use underpricing as a signal of their type (Ibbotson (1975)). Moreover, the composition of issuers may change over the cycle; if certain firms are more information sensitive, this could contribute to the observed pattern. To test these hypotheses, I absorb any cross-sectional variation across firms with firm fixed effects

[16] The measure is based on 85 existing indicators that use data on variables such as production, income, employment, consumption, and sales. It is constructed to be mean zero with a standard deviation of one, where positive values indicate growth rates above trend.

[17] The GZ credit spread is calculated monthly as the arithmetic average of credit spreads on outstanding bonds in any given month. Given the correlation between GZ and CFNAI is typically higher, this coefficient illuminates how the regression that is conditional on issuance generally understates the cyclicality of the cost of capital.

Table 1: Issuance premiums are higher in bad times

	(1) Baseline	(2) Issuer controls	(3) UW Info	(4) Firm FE	(5) GZ spread (bps)
Economic activity	-1.023***	-1.069***	-1.070***	-1.036***	-8.656***
	(0.0929)	(0.0945)	(0.0964)	(0.0656)	(0.205)
Issuance range / spread			-0.167	-0.297*	
			(0.142)	(0.151)	
Credit rating (log)	-14.35***	-16.02***	-16.07***	-14.41***	
	(0.446)	(0.468)	(0.478)	(1.759)	
Bond size (log)	0.771***	0.831***	0.860***	1.162***	
	(0.102)	(0.109)	(0.105)	(0.146)	
Tenor (years)	-0.0926***	-0.0933***	-0.0928***	-0.0722***	
	(0.00605)	(0.00617)	(0.00632)	(0.00445)	
Debt / assets		-2.791***	-2.739***	-4.568***	
		(0.550)	(0.577)	(1.418)	
Cash / assets		1.196	0.907	7.230***	
		(0.785)	(0.771)	(2.569)	
Operating profit / assets		32.66***	31.91***	23.15***	
		(6.338)	(6.403)	(6.459)	
Firm FE				✓	
Underwriter FE			✓	✓	
Observations	17134	17134	17113	17074	24598
R-squared	0.136	0.141	0.149	0.479	0.0673

Notes: Dependent variable in regressions (1) through (4) is issuance premium, measured in basis points. Dependent variable in regression (5) is the GZ spread, as defined on a monthly basis in Gilchrist and Zakrajšek (2012). Independent variable of interest is economic activity as measured by the CFNAI monthly index, collected from the Chicago Federal Reserve, which is designed to be mean zero with a standard deviation of one. Bond controls include issuer credit rating (log), size of bond (log), and tenor in years. Firm controls in regressions (2) through (4) include the prior quarter cash to total assets ratio, total debt to total assets ratio, and operating profit to total assets ratio. Regressions (3) and (4) control for bond-level issuance range as a proportion of the final issuance credit spread. Regressions (3) and (4) include underwriter fixed effects. Regression (4) includes firm fixed effects. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter level.

in the next regression, and find little change in the coefficient of interest.

In summary, I find that issuance premiums are countercyclical, and that this pattern is unlikely to be driven entirely by changes in fundamentals or information asymmetries. The finding is also robust to various specifications with different proxies for the business and credit cycle, including using dummy variables for the GFC and COVID-19 periods or the VIX (see Table 11 in the Appendix).[18]

[18] A potential alternative story is that the issuance premium is a constant percentage of total credit spreads, and the result here is simply a mechanical consequence of the well-known countercylicality of credit spreads. However, I

Moreover, this specification underestimates the countercyclical pattern because of selection bias: by conditioning on issuance, this analysis omits firms that did not issue in bad economic conditions because issuance premiums were too high for them. I will address this selection problem when modeling the firm's supply of capital in Section 4.

Increases in secondary market credit spreads in bad times, as documented in Gilchrist and Zakrajšek (2012), thus underestimate the countercyclicality of firms' costs of capital. This is important for firms because higher borrowing costs can deter issuance, dampening investment or reducing corporate liquidity. In the next section, I present observations about primary markets that will inform how to quantify the drivers and effects of issuance premiums.

3.2 Three facts about primary market investors

In this section, I discuss three features of primary markets. The first two are consistent with segmentation between primary and secondary markets: first, primary and secondary market investors differ from each other in trade size, fund size, and investor type; second, only a small fraction of primary market investors also participate in secondary markets. Third, in bad times, the share of investors that flips bonds from primary to secondary markets increases.

3.2.1 Primary market investors are different and trade in larger size

First, I find that participants in primary and secondary markets are not the same along observable characteristics. Primary market investors buy in bigger sizes and tend to be larger funds. In Figure 3a, I plot the distribution of trade sizes in the primary and secondary markets in the first 100 days following issuance, as reported by Enhanced TRACE. The distribution of purchase sizes in primary markets is larger than that in secondary markets.

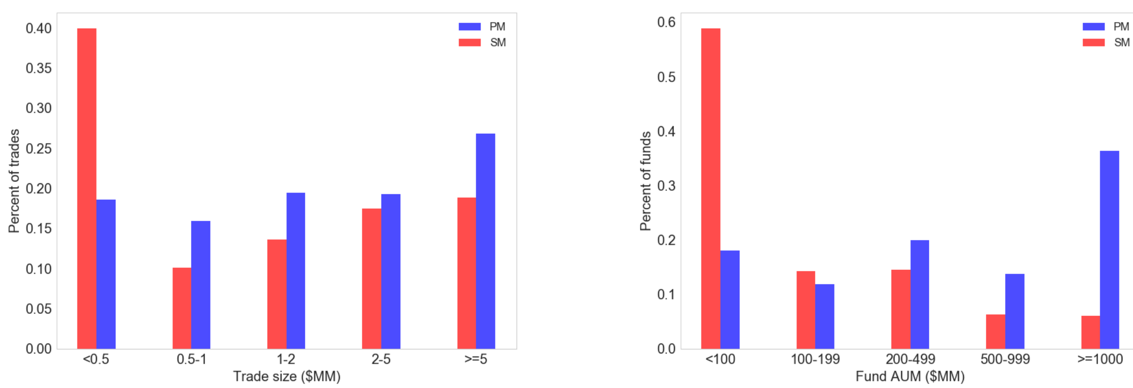
Moreover, I show a size discrepancy between primary and secondary market insurance investors. I use the NAIC regulatory data and follow Nikolova et al. (2020) to identify primary market investments by insurers as any purchases on the offering date from an underwriter at the offering price. In Figure 3b I plot the distribution of assets under management for insurance funds that purchase

find in Table 10 that the same pattern of countercyclicality applies to the ratio of issuance premium to total credit spread. Another alternative story is that there is higher trading volatility in bad times. In unreported results, I add the standard deviation of prices within the first week following issuance as a control in the baseline regression, and the pattern still persists.

in the primary market versus those that purchase only in the secondary market: clearly, primary market insurers tend to be larger in fund size.

I expand the scope to include all insurance, mutual, and pension funds using eMAXX quarterly holdings data in the first quarter of a bond's life in Table 7.[19] I proxy for primary market purchases by considering the subset of bonds issued within the last seven days of quarter end.[20] I find that indeed, across these three fund types, only a subset of investors participate in primary markets, and this subset of funds is significantly larger in assets under management than their counterparts that participate in only secondary markets.[21]

Figure 3: Size differences between primary and secondary market investors



(a) Trade size comparison (TRACE)

(b) Insurer size comparison (NAIC)

Source: TRACE and NAIC
Note: The first panel shows the distribution of volumes for primary market versus secondary market "buy" trades (in the first 100 days), as reported by Enhanced TRACE for corporate bonds issued since 2000, cleaned by the Dick-Nielson filter (Dick-Nielsen (2014)). The second panel shows the distribution of the total assets under management for insurance investors (from NAIC) that participate in only (1) primary markets for corporate bonds in my sample (in blue) and (2) secondary markets for corporate bonds in my sample (in red).

Why might primary and secondary market investors differ? In the presence of search costs

[19]Insurance investors, mutual funds, and pension funds make up about 50% of bond holdings. Other investors include ETFs, hedge funds, banks, finance companies, and the rest of the world. Figure 9 in the Appendix shows the holders of corporate bonds based on the Federal Reserve Flow of Funds data. U.S. hedge funds are incorporated in "households", and non-U.S. hedge funds are incorporated in "rest of the world". In Q4 2020, all hedge funds held \$1.9 trillion of corporate and foreign bonds; 23% of the holdings are domestic hedge funds. See `https://www.federalreserve.gov/releases/efa/efa-hedge-funds.htm` for more information.

[20]To see if this subset of bonds is significantly different from bonds issued on other days within quarter, I report in Table 12 the distributions of various issuer and bond characteristics in the full sample versus those for bonds issued in the last seven days of the quarter.

[21]This finding is robust to defining the primary market as the subset of bonds issued within the last 1, 3, or 5 days of quarter end.

(Henderson and Tookes (2012)) and potential information asymmetries (Benveniste and Spindt (1989), Cornelli and Goldreich (2001)), underwriters benefit from having repeat relationships with investors, and tend to allocate to investors with whom they have profitable trading relationships (Nikolova et al. (2020)). A finite number of investor relationships would suggest that primary market participants are a subset of all investors and are more likely to be larger funds. I find both of these to be the case.

3.2.2 Most trading occurs right after issuance

Second, trading activity is concentrated in the days immediately following issuance. This separates primary market investors into two types. Most primary market investors are "buy-and-hold" types that rarely, if ever, participate in secondary markets. However, a small proportion of investors "flip" bonds within the first few days following issuance. These investors earn the short-term profit of the issuance premium. This fact is consistent with work by Goldstein and Hotchkiss (2020), Bessembinder et al. (2021), Cai et al. (2007), who also find that most trading activity occurs within the first few weeks after issuance.

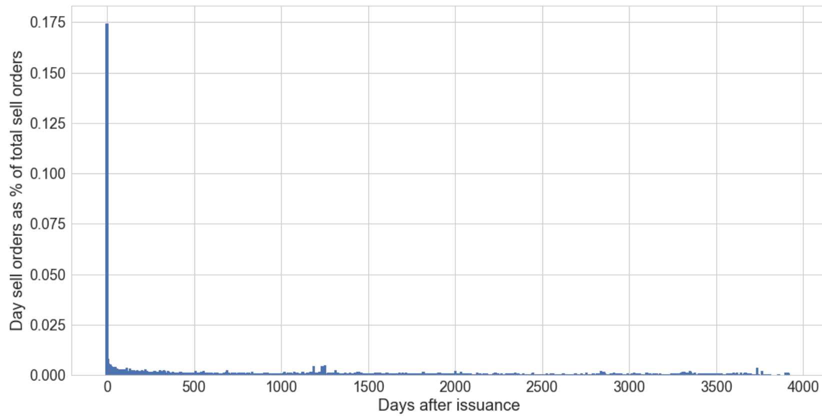
To illustrate this point, in Figure 4 I plot the timing of the share of all sell orders for a set of 10-year bonds issued in 2010. There is a spike in the share of sell trades in the first day following issuance (the "flippers"), followed by comparatively small trading volumes for the remaining life of the bond.[22]

Indeed, following the initial flurry of activity, corporate bond investors tend to hold the same bond over time. I compute the percentage of investors with reported holdings that also held that bond in the previous quarter and report the median across all bonds over the life of the bond in Figure 12. By the end of the second quarter after issuance, 84% of holdings are by investors that held the bond in the first quarter following issuance. The percentage is well over 90% for every quarter thereafter.[23] This dichotomy in post-issuance behavior suggests a difference in preferences

[22] This behavior is consistent across ratings categories; see Figure IA.1 in the Internet Appendix.

[23] There is some variation across fund types: insurance funds on average hold bonds for over 8 quarters, while the average holding period for mutual funds and pension funds is 4–5 quarters. See Table 13 for a summary of the investment behavior of the three fund classes. While the holdings data does not include all hedge fund holdings, aggregate data from the Flow of Funds shows a positive correlation between the share of short-term investors in primary markets and the share of overall corporate bond holdings attributable to hedge funds, suggesting that hedge funds are more likely to be short-term investors (see Figure 13). This is consistent with interviews with industry participants.

Figure 4: Evolution of sell trades for all 10-year bonds issued in 2010



Source: Enhanced TRACE.
Note: This figure reports the volume share of "sell" trades for each day in event time since issuance. It includes secondary market trades for USD non-financial corporate bonds issued in 2010 with initial tenor of 9–11 years. The y-axis shows the average across all bonds of the share of each day's sell orders as a percentage of total volume of sell orders over the life of the bond (defined as trades between 0 and 4000 days following issuance).

among primary market investors, likely arising from heterogeneous institutional funding needs. It also further segments primary and secondary markets: because a large proportion of primary market investors buy and hold, secondary market investors are excluded from holding a significant portion of these bonds.

3.2.3 More short-term investors participate in bad times

Third, I show that the share of short-term investors varies across the cycle. I run regressions of short-term investor participation in primary markets on various proxies for market downturns. I compute the share of short-term investors as the ratio of total secondary market sales reported in the first week following issuance in Enhanced TRACE to the total size of the bond. The average bond in my sample has a short-term share of 20%. I regress this share of short-term investors on the CFNAI, a proxy for economic conditions:

$$STshare_{bft} = \beta_1 EconActivity_t + \alpha_y + \alpha_u + \alpha_f + X_{bft}\gamma + \epsilon_{bft}, \tag{2}$$

where X_{bft} includes bond controls (tenor, rating, and size) to absorb any clientele effects along those dimensions, α_u represents underwriter fixed effects to absorb underwriter-specific bias towards short-term investors, α_y represents year fixed effects to absorb slow moving macro trends in investor participation, and α_f represents firm fixed effects. I report the results in Table 2. I find that worse macro fundamentals correspond to higher shares of short-term investors.

Why is there a shift towards short-term investors in downturns? In the second column, I test whether short-term investors are participating more due to worsening firm fundamentals, by including issuer fixed effects and issuer-specific time-varying characteristics: default probabilities derived from CDS trading and lagged cash and leverage ratios. The coefficient on economic activity is somewhat smaller but still significant, suggesting that some of the variation in the proportion of short-term investors is driven by changing fundamentals.

Next, I test a demand-driven story: in bad times, institutional investors as intermediaries are more capital-constrained (He and Krishnamurthy (2013)), and short-term investors may be more or less constrained than long-term investors. In the last column of Table 2, I include (1) the TED spread, computed as the difference between LIBOR and the U.S. Treasury bill rate, as a proxy for dealer funding costs (Friewald and Nagler (2019)), and (2) the dealer intermediated volume ratio, computed as the ratio of weekly buy volume from customers to weekly buy volume from dealers, as a proxy for dealer balance sheet capacity (Boyarchenko et al. (2021)). The inclusion of these controls somewhat reduces the magnitude of the countercyclical pattern, suggesting that some of the pattern is demand-driven. The coefficient estimates on both metrics are consistent with the story that short-term investors are less capital-constrained than long-term investors in bad times: higher short-term shares are correlated with higher TED spreads and higher intermediated volume. These results suggest that when long-term investors are more constrained, short-term investors act as a stopgap.

Relatedly, in Figure 5 I observe a positive correlation between issuance premiums and the share of short-term investors. This correlation holds even when controlling for firm, underwriter, and year fixed effects. Intuitively, short-term investors directly realize the profits from the issuance premium, so their increased participation in bond issues with high issuance premiums is expected.[24]

[24] This relationship is similar to the well-documented correlation between IPO underpricing and flipping activity. See, for example, Aggarwal (2003).

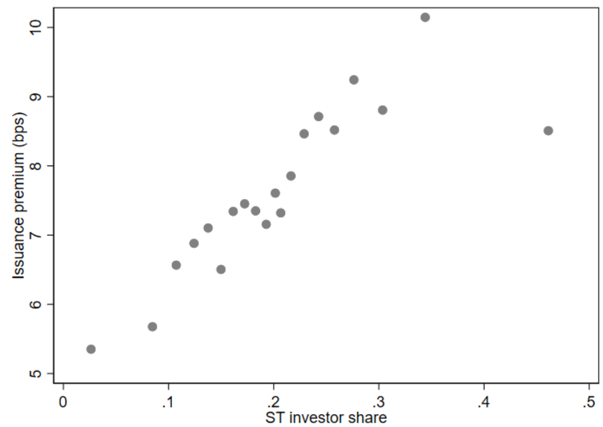
Table 2: Increased short-term investor participation in bad times

	(1) Short-term share	(2) Firm fundamentals	(3) Demand-side effects
Economic activity	-0.00200***	-0.00138***	-0.00118***
	(0.000378)	(0.000385)	(0.000411)
Probability of default		1.203***	1.158***
		(0.122)	(0.129)
Bond size (log)	-0.0105***	-0.0129***	-0.0135***
	(0.00281)	(0.00282)	(0.00283)
Tenor (years)	0.00246***	0.00252***	0.00254***
	(0.000136)	(0.000140)	(0.000139)
Credit rating (log)	-0.0789***	-0.00721	-0.00541
	(0.0170)	(0.0224)	(0.0224)
Cash / assets		0.0651***	0.0623***
		(0.0203)	(0.0222)
Debt / assets		-0.0315	-0.0234
		(0.0242)	(0.0250)
TED spread			0.0112**
			(0.00446)
Intermediated volume (dealer capacity)			-0.00950***
			(0.00166)
Year FE	✓	✓	✓
Firm FE	✓	✓	✓
Underwriter FE	✓	✓	✓
Observations	14001	14001	14001
R-squared	0.309	0.313	0.314

Note: Dependent variable is the share of short-term investors for each bond, measured as the selling activity in the first week following issuance divided by the size of the bond issuance. Independent variable of interest is the CFNAI monthly index, a proxy for economic activity. Bond controls include size of bond (log), tenor in years, and issuer credit rating (log). Regression (2) adds the following firm controls: probability of default as computed using CDS trading, the prior quarter cash to total assets ratio, and the prior quarter total debt to total assets ratio. Regression (3) adds the following market level controls: the TED spread (the difference between LIBOR and the U.S. Treasury bill rate) and the dealer intermediated volume ratio, computed as the ratio of weekly buy volume from customers to weekly buy volume from dealers. All regressions include year, firm, and underwriter fixed effects. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter.

In summary, this section highlights two key features of corporate bond issuance that set primary and secondary markets apart: primary and secondary market investors are different along observable dimensions, and many primary market investors buy and hold and thus do not participate in secondary markets. Moreover, I find that these short-term investors participate more in bad times. Together, these facts suggest that the preferences and decisions of agents in primary markets may

Figure 5: Higher issuance premiums $\iff$ more short-term investors



Note: The figure shows a binned scatter plot of the share of the bond sold within the first week on issuance premium, conditional on the short-term share being between 0 and 1. It includes controls for issuer credit rating, bond tenor, bond size (log), and U.S. Treasury yields, as well as year, firm, and underwriter fixed effects.

have important implications for issuance outcomes across the cycle. In the next section, I present the model that I will use to evaluate the magnitudes of these effects.

4 Model

In this section, I develop a structural model of the corporate bond issuance market that predicts equilibrium firm supply of new bonds, investor demand for bonds in the primary market, and underwriter issuance decisions.

The institutional details in Section 2 and stylized facts in Section 3 motivate the model's assumptions. In particular, (1) there are two components of credit spreads that make up firms' costs of capital; (2) there is some segmentation between primary and secondary markets; (3) primary market investors exhibit two mutually exclusive behaviors: selling immediately into the secondary market, or buying and holding; and (4) underwriters choose final credit spreads by sharing rents between investors and issuers.

4.1 Model setup

There are four types of agents in my model: firms f, two types of investors $h \in \{ST, LT\}$ (where ST stands for "short-term" and LT stands for "long-term"), and an underwriter u. Firms choose how much to raise in bond markets, investors choose how much to demand in the primary market, and an underwriter (dealer) chooses the final credit spread on new securities to split rents between issuers and investors.

The timing of events is as follows. First, firms choose a quantity Q^S to issue of a bond b in market t based on an underlying supply curve. Second, primary market investors (indexed by i) optimally choose an amount z_{ib} to purchase based on credit spreads and bond characteristics X_b. In aggregate, primary market investors have demand Q^D for bond b. Finally, the underwriter chooses the credit spread r_b relative to the risk-free rate at which to price the new bond, subject to sufficient investor demand and firm participation. Uppercase Q denotes dollar amounts of bonds, in millions, and lowercase q indicates the corresponding logged amounts. All proofs are in the appendices.

4.1.1 Firms' supply of bonds

Each firm has an underlying supply of bonds that depends on the firm's characteristics, macro fundamentals, and the cost of capital it expects to receive in the market. A firm's cost of capital for a given bond b is the risk-free rate plus the credit spread. The credit spread has two components:

$$r_b = r_b^{PM} + r_b^{SM}, \tag{3}$$

where r_b^{PM} is the issuance premium and r_b^{SM} is the expected credit spread for the bond once it begins trading in secondary markets.

The firm's latent supply of bonds is given by

$$q^* = \gamma_r r_b + \gamma_Z Z + e, \tag{4}$$

where γ_r is the firm's sensitivity to credit spread r_b, γ_Z is the vector of loadings for each of the firm and macro characteristics Z, and e is a normally distributed random shock to its supply of bonds.

The firm faces fixed costs to issue securities (see, for example, Bolton et al. (2013)). Thus, it will only issue if its latent demand for capital q^* is above a threshold C; that is,

$$q^S = \begin{cases} q^* & \text{if } q^* > c, \\ 0 & \text{otherwise,} \end{cases} \tag{5}$$

where $c = \ln C$.

Based on a standard tobit, the expected bond issuance supply for firm f is

$$E[q^S|Z, q^* > c] = \gamma_r r + \gamma_Z Z + \sigma\Big[\frac{\phi((\gamma_r r + \gamma_Z Z - c)/\sigma_e)}{\Phi((\gamma_r r_f + \gamma_Z Z - c)/\sigma_e)}\Big]. \tag{6}$$

The expected amount issued conditional on issuing is a linear combination of credit spreads, firm characteristics, and an additional term that accounts for selection bias into issuing. See Appendix B for details.

Finally, I derive from (4) an expression for $\bar{r}_b$, the highest credit spread at which a firm will issue amount q^S:

$$\bar{r}_b = \frac{1}{\gamma_r}\big[q^* - \gamma Z - e\big]. \tag{7}$$

This will be useful when simualating counterfactual equilibria.

If firms prefer lower credit spreads ($\gamma_r < 0$), then they will have a higher reservation credit spread when they have a greater propensity to issue: that is, when e (shock to supply of capital) is higher or when the realization of γZ is greater (worse fundamentals).

4.1.2 Investors' demand for bonds

Investors i of type $h \in \{ST, LT\}$ choose to allocate each dollar to the bond b in market t that maximizes expected CARA utility. For investor i, the problem is

$$\max_{b \in \{0,1,\ldots,B+1\}} U_{ibt} = E\Big[-\exp\Big(-\frac{1}{k_h} R_{hbt}\Big)\Big], \tag{8}$$

where investors have absolute risk aversion $1/k_h$, so higher k_h corresponds to lower risk aversion, and bond b has stochastic returns

$$R_{hb} \sim N(\mu_{ihbt}, \sigma_t^2) \tag{9}$$

in excess of the risk-free rate. Note that I assume that σ_t^2 is constant for all bonds within a market t. I parameterize the mean return μ_{ihbt} as follows:

$$\mu_{ihbt} = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt} + \epsilon_{ihbt} =: \delta_{hbt} + \epsilon_{ihbt}, \tag{10}$$

where α_h is the loading on r_{bt}^{PM}, $\alpha_{h,SM}$ is the loading on r_{bt}^{SM}, and β_h represents the loadings on the vector X_b of bond and firm characteristics. To allow for components of bond-specific demand that are unobserved by the econometrician, such as perceived risk tolerance of firm management or brand recognition, I include the term ξ_b, which is common to all investors. Finally, I include any unobserved investor-bond-specific characteristics in ϵ_{ihb}. For example, ϵ_{ihbt} may include the covariance of bond b with the rest of investor i's portfolio (from classic portfolio theory), investor-specific beliefs about a firm's performance, or the liquidity and performance of the investor's portfolio.[25] I make the assumption that the investor-bond error, ϵ_{ihbt}, has a Type 1 extreme value distribution. This is a standard assumption in the discrete choice demand estimation literature (Berry (1994), Berry et al. (1995)).

Investors allocate a dollar towards bond b if their utility for bond b exceeds the utility of all other bonds $m \neq b$ in the same market: $U_{ibt} > U_{imt}$ $\forall m \neq b$. In addition to choosing among the bonds in each market, investors can also choose the risk-free asset, which returns zero. Exploiting the property of the extreme-value distribution, the choice probability for investor i of type h to invest a dollar in bond b is given by the following expression:

$$s_{hbt} = \frac{\exp\left(\alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt}\right)}{\exp\left(\frac{\sigma_t^2}{2k_h}\right) + \sum_m \exp\left(\alpha_h r_{mt}^{PM} + \alpha_{h,SM} r_{mt}^{SM} + \beta_h X_{mt} + \xi_{hmt}\right)}, \tag{11}$$

where the denominator is the sum of the exponential utilities from investing in (i) the risk-free asset and (ii) all other bonds issued in the same market. Intuitively, more dollars are allocated to the risk-free rate if volatility of bonds is higher.

[25] Chen et al. (2010) show empirically that funds with illiquid investments are sensitive to larger outflows based on past poor performance. This is an investor-specific shock that would impact demand for a given bond.

The demand for bond b is the sum of choice probabilities over investor types:

$$Q_{bt}^D = \sum_h s_{hbt} M_{ht}, \tag{12}$$

where M_{ht} is the total volume of type-h investor dollars in market t.

4.1.3 Underwriters

The usual equilibrium notion of setting quantity supplied equal to quantity demanded is insufficient in primary markets, given the empirical observation that bonds are often oversubscribed. Thus, to close the model, I introduce underwriters who select an equilibrium credit spread subject to market clearing.

Underwriters are risk-neutral profit-maximizing agents. They serve two clients: corporate issuers, who pay an ex-ante fixed commission to the underwriter, and investors, who buy primary market securities and engage in secondary market trading with the underwriter as a dealer. It is well-documented that underwriters may extract rents from issuers to favor investor clients.[26] However, since underwriting is a repeat business, the underwriter cannot extract too much from issuers. Thus, underwriters choose credit spreads to split gains from trade between issuing firms and primary market investors.

The investors' gains from trade are $Q(r_{bt} - r_{bt}^*)$, where r_{bt} is the actual issuance credit spread and r_{bt}^* is the counterfactual competitive equilibrium credit spread, taking Q^S as given. The firm's gains from trade are $Q(\bar{r}_{bt} - r_{bt})$, where $\bar{r}_{bt}$ is the highest credit spread at which the firm would still be willing to issue Q.

The underwriter favors investors to the extent η, and thus solves the following maximization problem, where Q drops out because it is a constant:

$$\max_{r_{bt}} \ \pi = (r_{bt} - r_{bt}^*)^{\eta} (\bar{r}_{bt} - r_{bt})^{1-\eta}. \tag{13}$$

[26]For example, underwriters may prefer regular investors that participate frequently in underwriting markets and provide valuation information and stability (Benveniste and Spindt (1989)); they may also favor large investors that provide additional revenue from trading or other services (Henderson and Tookes (2012), Nikolova et al. (2020), Flanagan et al. (2019)). Recent findings by Goldstein and Hotchkiss (2020) show that underwriters have market power in secondary markets given information advantage from participating in primary markets.

Differentiating (13) and applying the first-order condition yields

$$r_{bt} = \eta \underbrace{\bar{r}_{bt}}_{\text{Firm's reservation}} + (1-\eta) \underbrace{r^*_{bt}(Q_D, Q_S)}_{\text{Investors' reservation}} . \tag{14}$$

That is, underwriters select a credit spread that is between the firm's reservation credit spread and the investors' reservation credit spread. The more the underwriter favors the investors (the closer η is to 1), the closer the new issue credit spread is to the firm's reservation credit spread. If the underwriter favors firms fully ($\eta = 0$), then the new issue credit spread is the value of r^* for which demand is equal to supply.

This expression shows that new issue credit spreads are proximately a function of the firm's reservation credit spread (7), quantity supplied, and quantity demanded. Quantity demanded, as shown in the solution to the investors' problem (12), is a function of bond characteristics, risk aversion, and demand parameters. Quantity supplied and reservation credit spreads, from the firm's problem, are functions of firm characteristics. Exactly how these characteristics enter into the new issue credit spreads depends on parameter values, which I will estimate in the next section.

5 Estimation

5.1 Estimating the firm's supply parameters

In this section, I describe the estimation and identification for the firm's supply curve for bonds. For firm controls Z, I include the following: (i) the volume of bonds coming due in the following three months, logged, given that firms may issue when there are upcoming maturities (Leland and Toft (1996)); (ii) firm characteristics—credit rating, previous-quarter cash-to-assets ratio, leverage, and profitability—given that these may impact issuance decisions; and (iii) the risk-free rate and a proxy for macroeconomic conditions (the CFNAI), given that favorable market conditions may also encourage bond issuance (Ma (2019), Mota (2020)). For firms that did not issue in a given quarter, I use the most recent issuer rating and an average tenor of 10 years (the median bond term). I also include issuer fixed effects to ensure that I am capturing how each firm makes its own decisions over time. I allow for left-censoring at $C = \$100$ million, and $c = \ln C$, given fixed costs of issuance and the empirical observation that issuance is lumpy: firms will issue zero in most quarters and a large amount in a few quarters.

The primary empirical challenge in identifying how firms respond to changes in credit spreads is endogeneity. On one hand, a reduction in credit spreads may increase the amount that firms wish to issue (e.g., Ma (2019) and Mota (2020) for bonds, and Bolton et al. (2013) and Baker and Wurgler (2002) for general external financing). However, a coefficient estimated from regressing quantity supplied on credit spreads could be biased by reverse causality. If firms decide to lever up, this could drive credit spreads upwards as investors' perceptions of firm fundamentals deteriorate. Quantifying the causal impact of credit spread changes on firm issuance decisions thus requires investor perceptions of firm fundamentals, which are inherently unobservable, to be held fixed.

To overcome this issue, I use a unique feature of the new dataset to show that firms respond to changes in credit spreads. In a subset of bond issuances (16% of the sample), firms change the size of the bond within the span of a day based on revised expectations of investors' demand curves. Because bond issuances are completed in one day, investor perceptions of firm fundamentals (and fundamentals themselves) are unlikely to change. I find that in some bond issuances, firms respond to unexpectedly low credit spreads by "upsizing," or increasing the quantity of bonds supplied to the market. The subsample of bonds that are upsized is not significantly different from the full sample of bonds (Table 16 compares the distributions of firm and bond characteristics in the subsample to those in the full sample).

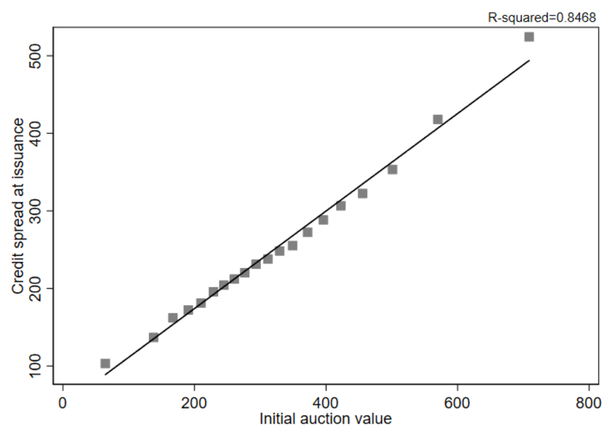
While I can observe the initial quantity of bonds that firms intend to issue, I do not directly observe the firms' initial expectations of credit spreads. Instead, I impute each firm's initial expectation of credit spreads from the initial *announced* credit spread in round $k = 0$, which I find is a good predictor of the final credit spread for round $k = 4$ for issuances that are not upsized. To show this, I run a regression of the final credit spread on the initial credit spread with controls for bond size, credit rating, and tenor and year fixed effects,

$$r_{bt,k=4} = mr_{bt,k=0} + \beta X_{bt} + \alpha_y + \epsilon_{bkt}, \tag{15}$$

where X_{bt} is a vector of controls that include amount issued (log), issuer credit rating, and tenor, and α_y is a year fixed-effects term to absorb any long-term trends in bond issuance practices. The regression shows that initial spreads are a good predictor of final spreads, with an R-squared of over 0.83 and a tight-fitting binscatter plot shown in Figure 6. For upsized bonds, I compute the predicted $E[r_{bt,k=4}|\text{no upsize}]$.

As expected, for upsized bonds, initial expectations of credit spreads exceed the final issuance credit spreads by a mean (median) of 10 (7) basis points. For bond issuances that are not upsized, the mean (median) difference between expected credit spread and final issuance credit spread is 0 (2) basis points. Firms respond to these positive surprises in credit spreads by increasing the quantity supplied of bonds: I show in Figure 14 that bigger declines in credit spreads correspond to larger increases in quantity supplied.

Figure 6: Correlation of initial price talk with final treasury spreads



Note: The y-axis shows the initial announced credit spread for a given bond. The x-axis shows the credit spread for a given bond. The model includes year fixed effects and controls for issuer credit rating, bond size (log), and bond tenor.

With the reasonable assumption that firm fundamentals are fixed over the course of one day, bond fixed effects absorb all endogenous firm-level variation and pin down an unbiased estimate of firm elasticities. I estimate the within-bond tobit that identifies γ_r simultaneously with a within-firm regression that allows me to estimate coefficients on time-varying firm characteristics that I take as exogenous. I do this for the whole sample of firm-quarters, and then for subsamples based on credit rating and time period (normal versus crisis) in order to estimate how elasticities change when firms have lower financial slack.

5.2 Estimating investor demand

In this section, I describe the estimation and identification for investor demand. For bond controls X_{bt}, I include (i) the prevailing risk-free rate, given that demand for bonds may be impacted by the supply and price of U.S. Treasury bonds (Krishnamurthy and Vissing-Jorgensen (2012)); (ii) bond duration, given that investors have heterogeneous preferences across the term structure (Greenwood et al. (2010), Vayanos and Vila (2021)); (iii) issuer credit rating, given that certain investors may have preferences or mandates for higher credit ratings (Donaldson and Piacentino (2018), Becker and Ivashina (2015), Kisgen and Strahan (2010)); (iv) bond size, given that investors may also prefer larger bond sizes due to liquidity and index eligibility (Calomiris et al. (2021)); (v) the monthly CFNAI to proxy for macro conditions; and (vi) the monthly weighted average bid–ask spread for the bond to proxy for liquidity, given that investors may prefer more liquid assets.

Note that equation (11) for s_{hbt}, the choice probability of bond b, has unobservable demand characteristics entering nonlinearly. I take the traditional approach as proposed by Berry (1994) to invert the choice probability into a linear function of the unobserved demand component ξ_{hbt}:

$$\ln(s_{hbt}) - \ln(s_{h0t}) = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt}. \tag{16}$$

Because $s_{hbt} = Q_{hbt}/M_{ht}$ by definition, I can rewrite the linear expression as

$$q_{hbt} = \alpha_h r_{bt}^{PM} + \alpha_{h,SM} r_{bt}^{SM} + \beta_h X_{bt} + \xi_{hbt} + \ln(s_{h0t}) + \ln(M_{ht}). \tag{17}$$

I assume the last two terms in (17) are common within a market, so I can absorb them with a market fixed effect (see Diamond et al. (2020)). Empirically, I use week fixed effects. I am assuming then that the set of bonds from which an investor chooses is fixed within each week. I estimate equation (17) across the two types of investors: $h \in \{ST, LT\}$.[27] To be able to compare the elasticities of the two investor types, I assume that the variance of unobservables for LT and ST investor demand is the same (Train (2009)).

I cannot directly estimate equation (17) with OLS, because there is potential endogeneity between the unobserved characteristics of the bond, ξ, and the yield r. Estimating demand properly

[27] Note that this modeling choice assumes quantity demanded for each investor type depends solely on size of market and the mean utilities for each investor type.

generally requires addressing two fundamental challenges: first, price is likely correlated with unobservables that affect demand, and second, demand for one good depends on prices and characteristics of other related goods (Berry and Haile (2021)).

To overcome this, I use an exogenous supply shifter: the variation in daily supply of new bonds issued by *other* firms in the same market, underwritten by other broker-dealers. I call this metric "crowdedness." I make two assumptions. First, I assume that newly issued corporate bonds are imperfect substitutes. This is reasonable, since bonds issued by large corporations have similarly stable, predictable cash flows, and default rates are historically very low. Second, I assume that the day of week on which each firm chooses to issue is reasonably random, and thus is orthogonal to the unobservables of other firms issuing on the same day. This assumption is based on industry interviews: a firm's specific issuance day may be influenced by the maturity date of existing debt, the progress of a liability management program, an acquisition, or even the management's ability to finish documentation necessary for issuance. Moreover, while one firm's underwriter may be able to advise the firm on the timing of other firms' issuance, that underwriter will not necessarily know the exact timing of bonds underwritten by other broker-dealers. With these assumptions, the random variation in other firms' bond supply acts as an exogenous supply shifter. Indeed, I find that more crowded markets have higher credit spreads, controlling for firm characteristics.

To account for slow-moving economy-wide trends in demand for capital, I include week fixed effects so the focus is on within-week variation. More sophisticated firms may find ways to issue on less crowded days; to deal with this potential concern, I include firm fixed effects. Finally, bigger broker-dealers may know about a larger proportion of issuance on any given day, so I include underwriter fixed effects. Specifically, I regress issuance premiums and credit spreads on crowdedness as follows:

$$IssPrem_{ufbt} = \beta_1 \ln(Crowded)_{uft} + \beta_2 \ln(Crowded)^2_{uft} + \alpha_w + \alpha_f + \alpha_u + X_{fbt}\gamma + \epsilon_{ufbt}, \quad (18)$$

where the subscript b represents the bond, f the firm, t the day, w the week, and u the underwriting bank. I compute crowdedness as the total bond issuance volume on the same day by other non-financial firms with no overlapping active underwriters. I include both the log and the squared log terms to allow for nonlinearities. For bond controls X, I include the same set of controls used in the demand estimation.

The coefficient on the log of crowdedness is statistically significant and positive: the more crowded a market, the higher the issuance premium and credit spread. The effect is nonlinear: as markets become more crowded, the effect becomes smaller. At a crowdedness of $2.5 billion, the effect becomes negative; however, only 4% of bonds are subject to such high levels of other issuance. Thus, an increase in supply of other firms issuing will generally increase a firm's cost of capital, consistent with an upward-sloping demand curve for bonds.

Table 3: Price impacts of supply shocks in primary markets

	(1) Issuance premium (bps)	(2) SM credit spread (bps)
Amount issued by other firms (log)	1.101***	5.391***
	(0.214)	(1.857)
Amount firm f issues day t (log sq)	-0.605***	-2.722***
	(0.0902)	(0.717)
U.S. Treasury yield	-0.280***	-6.485***
	(0.104)	(0.876)
Bond size (log)	1.116***	15.63***
	(0.143)	(1.118)
Credit rating (log)	-17.19***	-334.4***
	(2.923)	(16.07)
Tenor (log)	-0.381***	35.64***
	(0.0872)	(0.866)
Bid–ask spread	-0.407	2.015
	(0.361)	(1.956)
Bank FE	✓	✓
Week FE	✓	✓
Issuer FE	✓	✓
Observations	12613	12613
R-squared	0.591	0.869

Note: Dependent variable in the first regression is the issuance premium, measured in basis points. Dependent variable in the second regression is the secondary market credit spread on the newly issued bond, measured in basis points. Independent variables of interest is the amount issued by other firms, underwritten by other banks, in the same day (both logged and logged squared). Controls include U.S. Treasury yield for the duration of the bond, size of bond (log), issuer credit rating (log), tenor in years (log), and the monthly weighted average bid–ask spread. The model includes underwriter, issuer, and week fixed effects. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter level.

As additional instruments, I follow the standard IO literature (see Berry et al. (1995), Berry (1994)) and use the characteristics of other issuers (credit rating and previous-quarter cash ratios) in the same market. These characteristics are relevant because they affect the prices of other bonds, while satisfying the exclusion restriction because they do not directly enter into investors' utilities over bond b. I aggregate the instruments into vector Z_{bt} and estimate

$$E[\xi_{bt} Z_{bt}] = 0. \tag{19}$$

I can use the same framework to compute aggregate demand elasticities for each bond. The aggregate demand expression is

$$\begin{aligned} Q_{bt}^{D} = W_t\theta_t & \frac{\exp\left(\alpha_{ST} r_{bt}^{PM} + \alpha_{ST,SM} r_{bt}^{SM} + \beta_{ST} X_{bt} + \xi_{ST,b}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{ST}}\right) + \sum_{mt} \exp\left(\alpha_{ST} r_{mt}^{PM} + \alpha_{ST,SM} r_{mt}^{SM} + \beta_{ST} X_{mt} + \xi_{ST,m}\right)} \\ & + W_t(1-\theta_t) \frac{\exp\left(\alpha_{LT} r_{bt}^{PM} + \alpha_{LT,SM} r_{bt}^{SM} + \gamma_{LT} X_{bt} + \xi_{LTb}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{LT}}\right) + \sum_{mt} \exp\left(\alpha_{LT} r_{mt}^{PM} + \alpha_{LT,SM} r_{mt}^{SM} + \gamma_{LT} X_{mt} + \xi_{LT,m}\right)}, \end{aligned} \tag{20}$$

which I then log-linearize to

$$q_{bt}^{D} \approx q_t^{D} + \left(\theta_t\alpha_{ST} + (1-\theta_t)\alpha_{LT}\right) r_{bt}^{PM} + \left(\theta_t\alpha_{ST,SM} + (1-\theta_t)\alpha_{LT,SM}\right) r_{bt}^{SM} + \left(\theta_t\beta_{ST} + (1-\theta_t)\beta_{LT}\right) X_{bt} + \xi_{bt} + \zeta_t, \tag{21}$$

where θ_t is the market-wide share of the demand coming from short-term investors and W_t is the total wealth to be invested in period t. I include week fixed effects to absorb ζ_b. Empirically, I proxy for θ_t using the share of short-term investors in the primary market at the weekly level.

5.2.1 Comparison to buy-and-hold investors in SM

In order to compare preferences of PM and SM investors, I need demand elasticities for SM bond investors. For this, I adapt the method of using cross-sectional variation in institutional investment mandates from Koijen and Yogo (2019). I relegate the details of this method to Appendix A.5. I deviate from existing papers (e.g., Koijen and Yogo (2019) and Bretscher et al. (2020)) in an important way: I define each investor's investment universe, and thus the instrument, using *classes* of bonds, rather than individual securities. The reason for this is that there are many more unique bond securities than equity securities. Empirically, I define each class as a triplet of tenor, rating, and issuer sector. This classification is motivated by existing papers that document clientele effects among bond investors by rating category (Becker and Ivashina (2015), Gomes et al. (2020)) and by tenor (Vayanos and Vila (2021), Greenwood and Vayanos (2014), Guibaud et al. (2013)). There are

391 classes of bonds in my sample. I find empirical evidence that holders of corporate bonds tend to continue holding the same class of bond over time (see Table 14). I can then write the following moment condition, wherein log of latent demand is 0 given other investors' exogenous latent demand and observable characteristics:

$$E[ln(\epsilon_{itb}^{SM})|\hat{z}_{itb}, \mathbf{x}_{bt}] = 0 \tag{22}$$

The vector of control variables includes log rating, log number of years remaining, log amount of bond at issuance, probability of default, and bid–ask spreads.

5.2.2 Estimating the underwriter's solution

In this section, I describe how I estimate η, which represents how much underwriters favor investors relative to firms. First, I derive an expression for r^* (the counterfactual competitive equilibrium holding Q fixed) that is a function of estimated parameters and the data. I proxy for $\bar{r}$, the firm's outside option, using the initial credit spread announced in each issuance process. I plug these into the underwriter's solution (14), and solve for the value of η that minimizes the distance between the model-implied r_b and observed credit spreads.

I first write an expression for the counterfactual credit spread r^* that is dependent on observables, parameters, and the recovered latent demand:

$$r^* \equiv \{r : Q^D(r, X, \xi; \hat{\alpha}, \hat{\beta}) = Q^S\}. \tag{23}$$

I do not directly observe latent demand ξ, so I recover it from the observed quantity demanded at the observed credit spread for each bond, $q^D(r_b^o)$, using equation (21). This gives me an expression $\xi_b(q(r_b^o), X, \hat{\alpha}, \hat{\beta})$. I plug this into (23) and get

$$r_b^o - r_b^* = \frac{q^D(r_b^o) - q^S}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}. \tag{24}$$

This expression has an intuitive interpretation: the amount by which the observed new issue credit spread exceeds counterfactual competitive equilibrium credit spreads is a function of how much observed demand exceeds supply, scaled by the weighted-average demand elasticities of investors.

I can then write the empirical analogue of the underwriter's solution (14):

$$r_b = \eta \bar{r} + (1-\eta)\Big(\frac{q^S - q^D(r_b^o)}{\alpha_1 \theta_t + \alpha_2(1-\theta_t)} + r_b^o)\Big). \tag{25}$$

Using the estimated parameters from the demand side, I solve for the value of η that minimizes the distance between model-implied credit spreads and observed credit spreads.

5.3 Parameter estimates

Table 4 presents my estimates of demand-side parameters for primary market investors. The first column reports estimates for short-term primary market investors, and the second column reports estimates for long-term primary market investors. Within primary markets, short-term investors are more elastic to issuance premiums than long-term investors. A one-basis-point increase in issuance premiums will increase short-term investor demand by 7% and long-term investor demand by 3%. Demand elasticities over SM credit spreads are not significantly different from zero for short-term investors. Both investor types have higher demand for larger bonds and more liquid bonds (as proxied by lower bid–ask spreads).

I compare elasticities of short- and long-term investors in the last column of Table 4. Positive coefficients reflect a higher loading for short-term investors than for long-term investors. The difference between short-term and long-term elasticities over issuance premiums is positive and significant. Short-term investors are more likely to purchase more liquid bonds, as this improves their ability to exit their positions. Short-term investors also participate more when macro fundamentals are weak. Surprisingly, they are more likely to purchase longer-duration bonds, potentially reflecting the relative ease of flipping longer-duration bonds, which tend to be more liquid. Long-term investors prefer better-rated bonds than short-term investors.

Demand elasticities of secondary market investors are summarized in Table 15. The coefficients on credit rating, default probability, and bid–ask spreads have the expected signs: secondary market investors have positive loadings on higher-rated, less risky bonds that are more liquid. To compare PM and SM elasticities, note that the overall elasticity of each PM investor type is the average of the elasticities over issuance premium and the SM credit spread, weighted by the share of the overall credit spread that is due to the issuance premium. Short-term PM investors are more elastic to overall credit spreads than SM investors.

Table 4: Primary market estimates: full sample

	(1) Qd short-term (log)	(2) Qd long-term (log)	(3) Qd(ST) / Qd(LT)
Issuance premium (bps)	0.0728***	0.0335***	0.0393***
	(0.0124)	(0.00817)	(0.0107)
SM credit spread (bps)	-0.00205	0.00157	-0.00362
	(0.00269)	(0.00154)	(0.00234)
US Treasury yield	0.00401	-0.00832	0.0123
	(0.0248)	(0.0115)	(0.0238)
Bond size(log)	0.525***	0.607***	-0.0821
	(0.0552)	(0.0298)	(0.0495)
Credit Rating (log)	-0.504	0.867	-1.371*
	(0.907)	(0.555)	(0.759)
Tenor (log)	0.462***	-0.0571	0.519***
	(0.0956)	(0.0509)	(0.0853)
CFNAI	-0.0494***	-0.00808	-0.0413***
	(0.0176)	(0.0121)	(0.0121)
Bid-ask spread	-0.372***	-0.0676***	-0.305***
	(0.0327)	(0.0192)	(0.0318)
Underwriter FE	✓	✓	✓
Week FE	✓	✓	✓
Issuer FE	✓	✓	✓
Observations	11182	11182	11182

Note: This table covers sample bonds issued 2010–2020 with the share of short-term investors between 0 and 1. Controls include issuance amount (log), issuer credit rating (log), tenor in years (log), the CFNAI monthly index, and the monthly weighted average bid–ask spread. Instruments include amount of bonds issued on the same day by other firms and underwritten by other broker-dealers (log), and average rating and cash balances of same-day bond issuers. The model includes bank fixed effects to account for cross-sectional variation in underwriter balance sheets and variation in expected rationing; week fixed effects to absorb trends in demand for capital; and firm fixed effects to account for cross-sectional variation in unobserved firm characteristics. Standard errors are clustered by bank. Observations are weighted by size of bond.

Table 5 presents my tobit estimates of supply-side parameters.[28] At average values of covariates,

[28] To interpret these estimates as the quantity response to a change in credit spread, I follow Wooldridge (2002):

$$\frac{\partial E[q|Z,r]}{\partial r} = \hat{\gamma}_r \Phi\left(\frac{\hat{\gamma}_r r + Z\hat{\gamma}_Z - c}{\hat{\sigma}_e}\right), \tag{26}$$

where $\Phi(\frac{\hat{\gamma}_r r + Z\hat{\gamma}_Z - c}{\hat{\sigma}_e})$ is the probability of issuance.

the firm responds to a ten-basis-point increase in credit spreads with a 2% decrease in issuance volumes. Firms have greater loadings on other covariates, such as the risk-free rate (see Mota (2020)) and macro and firm fundamentals (Bolton et al. (2013)), when deciding issuance volumes. The coefficients on other covariates are as expected: firms that are higher-rated, with more cash on their balance sheets and less leverage in the previous quarter, issue more. IG firms with higher profitability and more debt coming due in the next three months also issue more bonds. All firms issue more when U.S. Treasury yields are lower and macro fundamentals (as proxied by CFNAI) are weaker.

To test how supply elasticities change when firms have less financial slack, I estimate for the following subsets of bonds: bonds issued by A-rated firms or BBB-rated firms, and bonds issued during the GFC period (2008–2009), the COVID-19 period (2020H1), and the period between (2010–2019). I report results in Table 17. Lower-rated firms are less responsive to changes in credit spreads, and firms issuing during the GFC are similarly less elastic. These results are consistent with firms becoming less price sensitive when they are low in financial slack. Firms issuing in the first half of 2020 have higher elasticities than on average, but since this period overlaps with the Federal Reserve's announcement that it would intervene in bond markets, I cannot distinguish between issuance to improve financial slack and opportunistic issuance (e.g., Baker and Wurgler (2002), Ma (2019)), the latter of which would bias supply elasticities to be higher in absolute magnitude.

For the underwriter's problem, I get an estimate of $\hat{\eta} = 0.634$, with bootstrapped standard errors equal to 0.0076. Underwriters thus systematically favor investors over firms. This is consistent with the literature that finds that underwriters value relationships with investors and that such relationships benefit the process of underwriting (Henderson and Tookes (2012), Benveniste and Spindt (1989), Nagler and Ottonello (2020)). Institutional investors are much more frequent participants in the corporate bond market, with the largest institutional investors[29] participating in primary markets every other day, while the largest corporate issuers[30] participate on at most one out of every 140 active market days. Many underwriting banks also act as dealers in the secondary market, and thus have relationships with bond investors that help them place bonds in primary markets (Hendershott et al. (2020), Goldstein and Hotchkiss (2012), Nikolova et al. (2020)). This

[29] Examples include Allstate and Pacific Life Insurance.
[30] Examples include Verizon, AT&T, and Apple.

Table 5: Firm supply estimates (standard tobit)

	(1) All issuance	(2) Amount issued by IG firms	(3) Amount issued by HY firms
PM Credit spread (bps)	-0.00221***	-0.00431 ***	-0.00203 ***
	(0.0002)	(0.0002)	(0.0004)
US Treasury Yield	-0.669***	-0.829***	-0.692***
	(0.133)	(0.227)	(0.224)
Credit rating	-2.853**	-1.031	-3.176
	(1.188)	(1.364)	(1.953)
Cash/Assets last qtr	-7.195***	-12.05***	-0.729
	(1.452)	(3.384)	(2.101)
CFNAI	-0.225***	-0.238***	-0.260
	(0.0829)	(0.0469)	(0.179)
Leverage last qtr	-1.262*	-2.183**	-1.500
	(0.665)	(1.096)	(1.374)
ROA last qtr	8.225*	18.78**	-2.805
	(4.424)	(9.362)	(4.698)
Amount due in 3 months	0.0166	0.0293**	-0.0422
	(0.0104)	(0.0134)	(0.0472)
Observations	20711	14688	6023

Note: This table covers sample bonds issued 2000–2020. Observation is by firm-quarter. Standard errors are clustered at the firm level. Standard tobit estimation is left-censored at log of $100 million. First regressor is estimated in a simultaneous within-bond estimation. Issuance volume is in logs.

potential conflict of interest may manifest in underwriters helping investors profit at the expense of issuers.[31] While underwriters also earn revenue from firms through mergers and acquisitions advisory and securities underwriting, revenues from trading with investors are typically higher than those from corporate-facing activities.[32]

[31]This behavior has been documented in many papers, both in equity markets (Benveniste and Spindt (1989), Cornelli and Goldreich (2001), Cornelli and Goldreich (2003), Jenkinson et al. (2018)) and in corporate bond markets (Nikolova et al. (2020), Goldstein and Hotchkiss (2020)). It is consistent with recent papers on incomplete competition among brokers in financial markets (Robles-Garcia (2019), Wang et al. (2020)).

[32]In Q1 2021, the twelve largest broker-dealers reported $29 billion in revenue from trading (including fixed income, commodities, and currencies) and $17 billion from investment banking. Source: "Global investment banks post highest H1 revenue in decade—Coalition Greenwich", September 17, 2021, `https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/global-investment-banks-post-highest-h1-revenue-in-decade-8211-coalition-greenwich-66632606`.

6 Counterfactuals

I return now to the motivating fact that issuance premiums spike in bad times: what drives this pattern? Because issuance markets are segmented from secondary markets, issuance prices are subject to shifts in supply and demand. In bad times, there are investor outflows (Falato et al. (2020)) and reductions in intermediary risk-bearing capacity (Gilchrist and Zakrajšek (2012)) that reduce investor demand for bonds. This naturally increases issuance premiums (decreases prices), just as a reduction in demand for any normal good will reduce prices. At the same time, firms' willingness to pay increases during downturns as they become more desperate for liquidity (Acharya and Steffen (2020)). How much does each of these factors matter?

To answer this question, I first use the model, estimated parameters, and exogenous characteristics (economic activity, U.S. Treasury yields, and firm fundamentals) described in the previous sections to simulate a series of issuance premiums, endogenizing quantities and investor shares.[33] I allow firms to be less price-sensitive in bad times by assigning them the elasticity estimated from the GFC when economic activity is one standard deviation below average. I then run regressions of the simulated issuance premium on economic activity, controlling for bond characteristics (credit rating, amount, and tenor) and firm characteristics (prior-quarter leverage, cash-to-assets ratio, and profitability). I report results in Table 6. The first column shows that regressions in the model fit the regressions from the data (in Table 1) well. Next, I impose the same supply elasticity on firms throughout the cycle to see how changes in firms' price elasticity affect the cyclicality of issuance premiums. The pattern is tempered somewhat, by about 6%, indicating that the reduction in firms' sensitivity to credit spreads contributes to the cyclicality of issuance premiums.

To test the price impact of shifts in investor demand that are unrelated to observable bond and firm characteristics, I run a counterfactual that shuts down fluctuations in latent demand by setting the total investor volume in the market to the average across periods. I report results in the fourth column of Table 6. This counterfactual reduces the cyclical pattern by about 20%, highlighting the importance of investor demand to the cyclicality of firms' funding costs. A reduction in non-fundamentals-driven investor demand in bad times increases primary-market-specific credit spreads. This is similar to the finding of Gilchrist and Zakrajšek (2012) that constraints on intermediaries

[33] See Figure 15 for a visual of model fit, comparing the distribution of the short-term investor share in each bond issuance as simulated in the model to that of the underlying data.

increase the excess bond premium in bad times. Finally, I shut down time-series variation in each firm's willingness to pay by assigning all firm fundamentals the average value within-firm. This takes away the cyclical pattern altogether, suggesting that despite frequent oversubscription, firms are price-takers in issuance markets.

How do institutions impact the transmission of shocks? To answer this question, I run two additional counterfactuals on market structure. In the fifth column of Table 6, I shut down investor heterogeneity, assigning all investors the demand elasticities of long-term investors. This amplifies the countercylical pattern significantly, by over 48%. I will discuss the importance of investor heterogeneity further in the next section.

Finally, I run the counterfactual where underwriters favor firms and investors equally (this corresponds to setting $\eta = 0.5$ in the model). Many papers document that broker-dealers favor investors in the underwriting process, either to gather information (Benveniste and Spindt (1989)) or to maximize trading profits (Nikolova et al. (2020)). This well-known favoritism has led the SEC to open investigations into the underwriting practices of prominent broker-dealers.[34] Eliminating this favoritism in the simulation reduces the countercyclical pattern by nearly 30%, suggesting that underwriters' extraction of rents from firms amplifies the cyclicality of cost of credit. Because underwriters favor investors, when firms' willingness to pay increases, the effect on issuance premiums is more pronounced. Moreover, in the counterfactual where underwriters favor firms and investors equally, issuance premiums are on average 5 basis points lower. This highlights the importance of incorporating underwriter incentives into our understanding of primary markets.

6.1 Effects of investor heterogeneity

How do fluctuations in issuance premiums impact firm issuance? I find that this depends on what kinds of investors are participating in primary markets. In this section, I examine the impact of investor heterogeneity on bond prices and volumes.

The demand parameter estimates detailed in the previous section confirm the heterogeneity across investors: short-term investors have a much higher loading on issuance premiums than long-term investors, and both types of primary market investors are more elastic than secondary market

[34] "SEC probes Goldman and Citi bond allocations", February 28, 2014, https://www.ft.com/content/977f4dc2-a0b7-11e3-8557-00144feab7de.

Table 6: Counterfactual magnitudes of issuance premium cyclicality

	(1) Baseline	(2) Same firm elasticity	(3) Investor demand shocks	(4) Firm propensity to issue	(5) Homogeneous investors	(6) UW even split
Economic activity	-1.000***	-0.943***	-0.803***	0.0609	-1.486***	-0.710***
	(0.0404)	(0.0402)	(0.0387)	(0.193)	(0.0532)	(0.0305)
Firm controls	✓	✓	✓	✓	✓	✓
Bond controls	✓	✓	✓	✓	✓	✓
Underwriter FE	✓	✓	✓	✓	✓	✓
Observations	8262	8262	8262	8262	8262	8262

Note: Outcome variable is issuance premium, measured in basis points. Dependent variable is the monthly CFNAI index from the Chicago Federal Reserve. The model includes industry (NAICS2) and underwriter fixed effects. Controls include prior-quarter leverage, cash-to-assets ratio, and profitability as measured by operating income over total assets. Bond controls include tenor (log), rating (log), and bond size (log). Standard errors are clustered at the underwriter level.

investors. Short-term investors' stronger preference for issuance premiums reflects the difference in investment strategy: they have a shorter time horizon within which to make profits, so they care less about the remainder of the credit spread and the riskiness of the issuer. These comparisons imply two ways in which investor composition affects the cost of capital and access to credit. On the dark side, because short-term investors have a high loading on issuance premiums, a higher share of short-term investors means higher issuance premiums, all else being equal. On the bright side, the endogenous shift to a higher share of short-term investors in bad times maintains a higher level of equilibrium quantities than a counterfactual of only long-term investors. Below, I describe the counterfactual simulations I run to make these findings more concrete.

To show the impact of investor heterogeneity on average issuance premiums, I simulate an equilibrium that shuts down investor heterogeneity by assigning all primary market investors the elasticities of long-term investors. This reduces issuance premiums on average by 4 basis points, which corresponds to a \$2.1-million reduction in the firm's cost of capital on a median 10-year, \$650 million bond.[35] This means that the participation of short-term investors in primary markets represents a cost to firms on average.

Next, I consider how investor heterogeneity impacts the transmission of shocks to firms. I simulate a series of counterfactual equilibria in which firms face a negative shock to their cash-to-assets ratios equal to one standard deviation in the cross-section of Compustat firms, which is 3%. I add on a range of negative investor latent demand shocks from zero to the levels seen

[35] Assuming an 8-year duration on the 10-year bond, $\$2.1\text{MM} = 0.04\% \times \$650\text{MM} \times 8$.

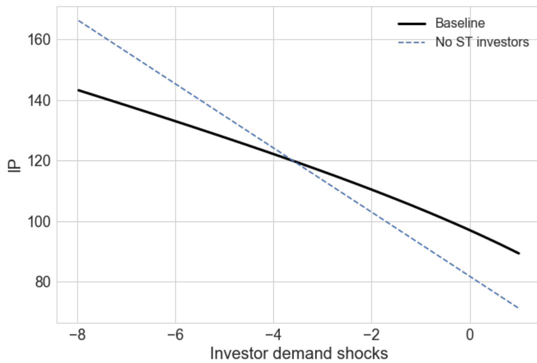
during the COVID-19 pandemic, representing, for example, large fund outflows. In Figure 7 I plot the equilibrium outcomes for a baseline economy that allows for endogenous changes in investor composition (in solid lines), and compare it to an economy where all primary market investors have long-term elasticities (in dashed lines). As firms supply more bonds, the increase in supply and their higher willingness to pay pushes issuance premiums up (Panel 7a). This encourages an increase in the share of short-term investors participating in primary markets (Panel 7b). As short-term investors endogenously enter, the issuance premium actually increases *less* than in the counterfactual without short-term investors. Moreover, as all primary market investors experience larger negative demand shocks, equilibrium quantities decrease less than in the counterfactual economy with only long-term investors (Panel 7c).

This mechanism sheds light on why I observe high participation by short-term investors and high issuance premiums in periods of market distress. Firms' higher willingness to pay drives up issuance premiums as underwriters continue to favor investors in splitting the surplus between firms and investors. This increases the share of short-term investors. Because short-term investor dollars are more price-elastic, they enter in larger quantities, pushing up quantity demanded. In the example of Nordstrom, discussed in the introduction, the firm's bond issue garnered significant demand despite deteriorating firm fundamentals. The large order book of $6 billion reflected high demand from short-term investors chasing issuance premiums. The presence of short-term investors allowed Nordstrom to raise sufficient capital at a time when it badly needed cash. This reflects the bright side of endogenously changing investor composition in primary markets: right when firms need capital the most, more price-elastic investors are attracted by higher issuance premiums and keep bond issuance volumes up.

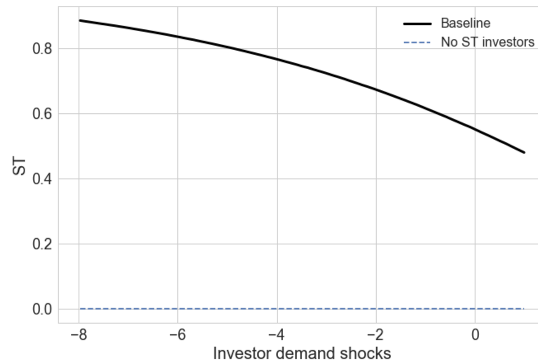
6.2 Policy implications

My results could inform the design of corporate bond purchase programs targeting primary or secondary markets. For example, in spring 2020, the Federal Reserve announced the creation of two credit facilities to purchase corporate bonds in primary and secondary markets. While the announcement of this program decreased yields and increased issuance volumes (Gilchrist et al. (2020), Boyarchenko et al. (2020)), as well as helping to stem large fund outflows (Falato et al. (2020)), the actual purchases were small and conducted exclusively in the secondary market.

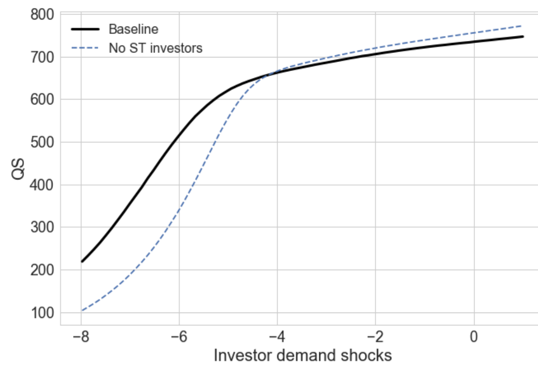
Figure 7: Counterfactuals: positive supply and negative demand shocks



(a) Issuance premiums



(b) Short-term share



(c) Quantity demanded

Note: The plots show counterfactual issuance outcomes in which firms face a negative shock to their cash-to-assets ratios equal to one standard deviation in the cross-section of Compustat firms, which is 3%. On the x-axis is a range of shocks to investor latent demand. The solid line represents counterfactual outcomes that allow for endogenous changes in the share of short-term investors. The dashed line represents counterfactual outcomes where all primary market investors have long-term elasticities.

Suppose the only consideration for selecting between primary and secondary market intervention was the impact on new issue prices and volumes, holding fixed announcement effects and political considerations. My estimated model makes it possible to quantify and compare the effects of purchases in primary versus secondary markets. For example, using the elasticity estimate from 2018 in Table 15, a purchase of 10% of a bond in secondary markets would cause a 56-basis-point decrease in secondary market credit spreads, all else being equal, and an additional drop of 3 basis points in issuance premiums. This would lead to a 10% increase in issuance volumes in equilibrium. A similarly sized purchase in primary markets, however, would have a relatively small effect of -2 basis points, with no significant increase in issuance. In other words, an increase in purchases in the primary market alone would not impact secondary market credit spreads; the only price impact would be via issuance premiums, and this would be very small, given how elastic primary market investors are to issuance premiums. The effect is even smaller if the share of short-term investors in primary markets increases, which is the case in bad times. Thus, when targeting corporate bond markets and aiming to maximize price effects, central banks should consider the relative elasticities between the primary and secondary markets, as well as the variation in primary market elasticities as short-term investors endogenously enter.

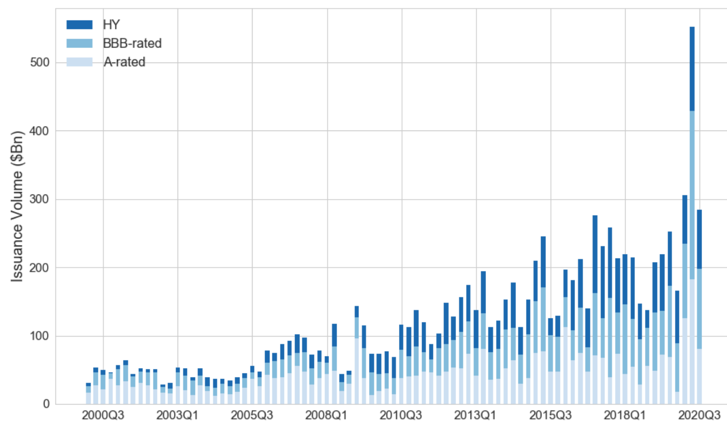
7 Conclusion

I present several new facts about the primary market for corporate bonds. I find model-free evidence that primary markets are subject to shocks distinct from those of secondary markets: in particular, the difference between primary and secondary market yields is greater in bad times, and this difference cannot be explained by issuer composition or firm fundamentals. The variation reflects segmentation between primary and secondary markets: firms cannot participate in secondary markets, while investors without underwriter relationships cannot participate in primary markets. Thus, the preferences of primary market agents – firms, investors, and underwriters – are directly relevant to the transmission of investor demand shocks to firms' costs of bond capital and access to credit.

To quantify the impact of shocks on cost of capital and issuance volumes, I propose and estimate an equilibrium model of corporate bond issuance using new micro-data on bond issuance. I find that short-term investors demand higher issuance premiums to participate in primary markets, but also help absorb large demand shocks and prevent credit spreads from spiking even further in bad times. This shift in investor composition highlights a self-correcting mechanism of capital markets: while issuance premiums drive costs of capital up even further in downturns, primary markets become more elastic and allow for smaller drops in issuance precisely when firms are least sensitive to credit spreads. These results have important policy implications both for regulation of broker-dealers and for future central bank interventions in corporate bond markets.

Additional Figures and Tables

Figure 8: Corporate bond issuance volumes



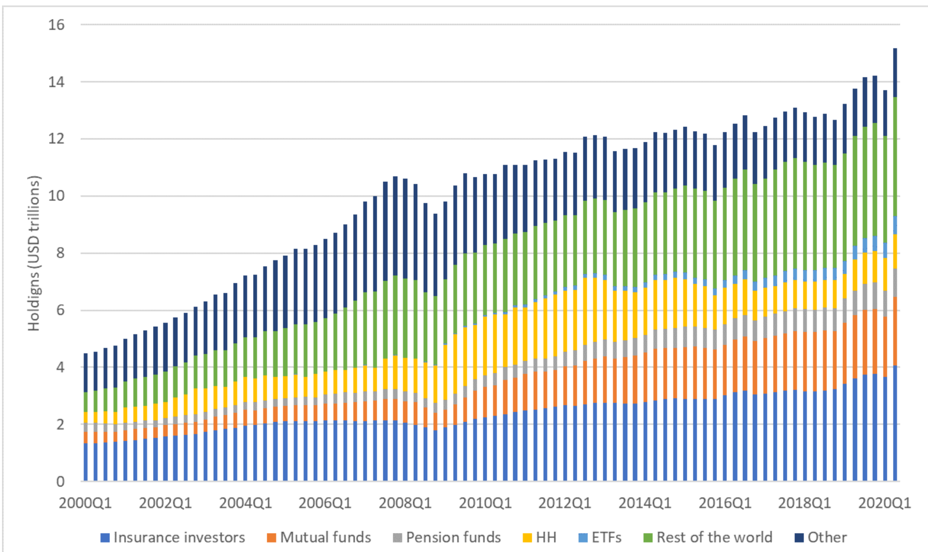
Source: Mergent FISD
Note: Includes USD corporate non-financial bonds greater than $100 million in size at issuance. Excludes convertibles, capital impact bonds, community investment bonds, PIK securities, and bonds issued by financials, sovereigns, supra-sovereigns, and utilities.

Table 7: Primary market participants are larger than secondary market participants

	Num unique funds	Average AUM (bn)	Median AUM (bn)
PM mutual funds	2781	1.48	0.20
SM mutual funds, not in PM (46%)	2398	0.65	0.08
PM insurance funds	1937	2.15	0.21
SM insurance funds, not in PM (52%)	2056	0.26	0.03
PM pension funds	259	1.18	0.25
SM pension funds, not in PM (63%)	450	0.58	0.14

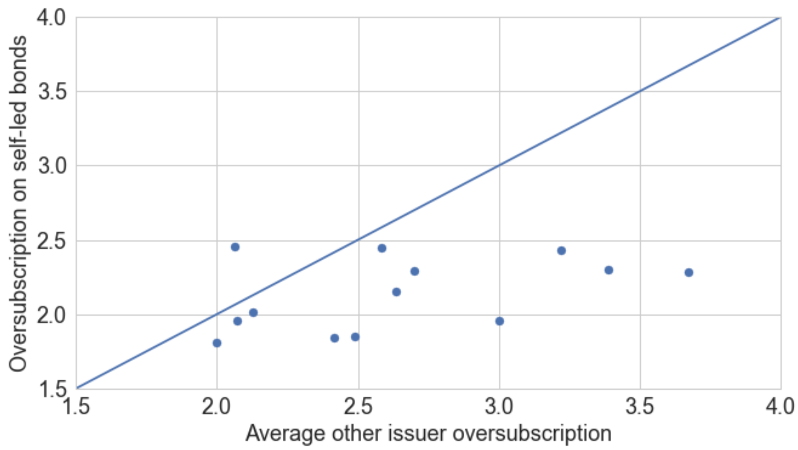
Source: Thomson Reuters eMAXX.
Note: This table reports the mean and median of most recent reported assets under management (in billions) for mutual funds, insurers, and pension funds that hold bonds in my sample in the first quarter end following issuance (at FUNDID level). I classify a fund as a primary market investor if they report holding the bond within seven days of issuance. I classify a fund as a secondary market investor if they hold the bonds in my sample but are not classified as a primary market investor. The percentage in parentheses reports the share of individual funds that hold bonds in the secondary market but not in the primary market.

Figure 9: Corporate bond holders



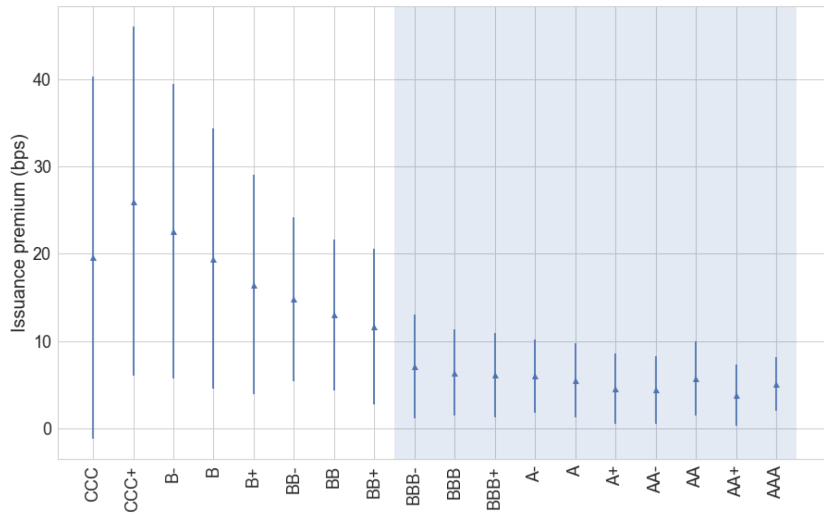
Source: Federal Reserve Flow of Funds.
Note: "HH" includes households and non-profit organizations. "Other" includes depository institutions, state and local governments, closed-end funds, finance companies, broker dealers, REITs, credit unions, GSEs, money market funds, and the federal government.

Figure 10: Banks have less oversubscription when they are both underwriter and issuer



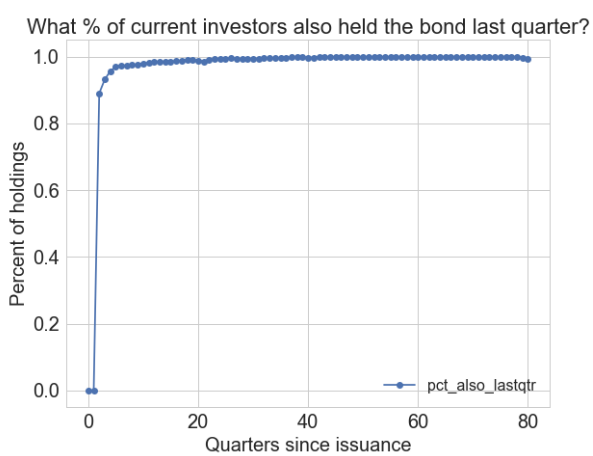
Note: Each dot represents a broker-dealer. The y-axis shows the average oversubscription on bonds issued and underwritten by broker-dealer u. The x-axis shows the average oversubscription on bonds underwritten by broker-dealer u but issued by other financial firms. To be included in the analysis, bonds issued by other financial firms must be within 2.5 years of bank u's average tenor and within 250MM of bank u's average bond size, must be rated within 1 notch of bank u's most recent highest rating, and must have ≤ 5 underwriters. The line is the 45-degree line: any dots on this line would indicate that the broker-dealer has the same oversubscription when underwriting its own bonds as when underwriting as comparable bonds issued by other firms. Dots below the line indicate broker-dealers achieving more oversubscription when underwriting bonds issued by other firms. Data is reported in Table 9.

Figure 11: Issuance premiums across ratings categories



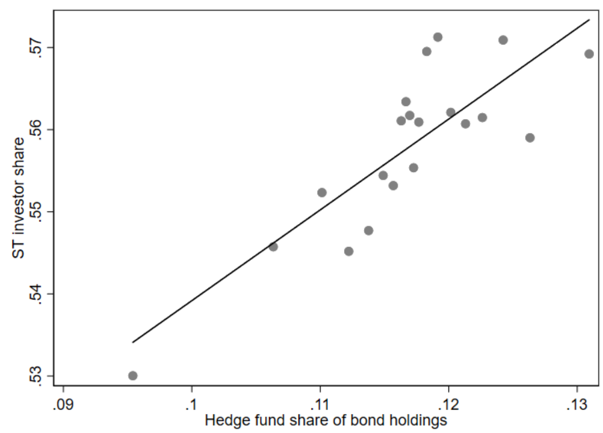
Source: Mergent FISD and Enhanced TRACE
Note: I aggregate credit ratings to the issuer level using Moody's, S&P, and Fitch issuer credit ratings at the time of issuance of each bond. I use the median if there are three ratings, and the minimum if there are two, as per Becker and Ivashina (2015).

Figure 12: Persistence of investor holdings



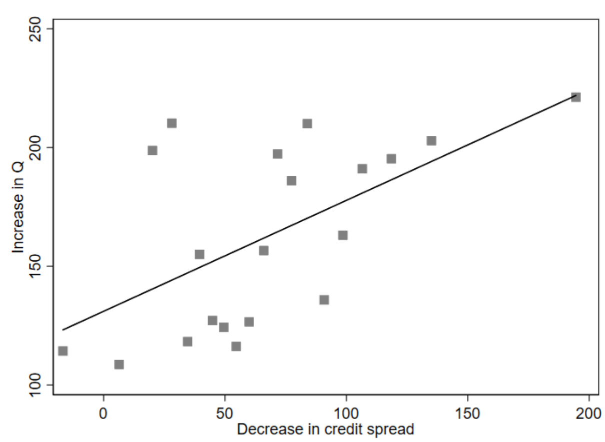
Note: Reports the median number of percent of investors (FUNDIDs) that also held the bond in the previous quarter.

Figure 13: Correlation: short-term investors and hedge fund share



Source: eMAXX and Enhanced TRACE
Note: The figure shows a binned scatter plot of percentage of hedge funds in Flow of Funds data on percentage of bond sold in the first 7 days. The model includes firm and underwriter fixed effects.

Figure 14: Greater increase in quantity supplied for upsized bond issuances when credit spreads are lower



Note: The y-axis shows the increase in amount issued for a given bond issuance. The x-axis shows the difference between the initial expected credit spread and the final credit spread. A positive x-axis value indicates that credit spreads were lower than the firm anticipated. I control for credit rating, tenor and year fixed effects.

Table 8: Primary market bonds: sample summary statistics

	Mean	Std Dev	Percentile 1	Median	Percentile 99
Full sample					
Credit Spread (bps)	263	222	29	185	1042
Coupon	4.88%	2.48%	0.00%	4.70%	12.00%
Yield to maturity	5.25%	2.84%	1.06%	4.90%	12.50%
Amount ($MM)	633	566	100	500	3000
Tenor (Years)	9.6	8.8	1.0	8.0	32.0
Credit rating	14.3	4.3	5.0	14.0	22.0
Issuance premium (bps)	7.7	11.6	-9.3	4.9	62.4
Money Left (MM)	6.0	14.8	-9.5	2.3	66.9
Pct sold first week	0.17	0.17	0.00	0.14	1.00
Issuance credit spread range (bps)	24	384	-2	10	76
Estimation sample					
Credit Spread (bps)	148	82	32	135	425
Coupon	3.44%	1.17%	0.88%	3.45%	6.24%
Yield to maturity	3.47%	1.16%	0.90%	3.49%	6.15%
Amount ($MM)	830	633	250	650	3000
Tenor (Years)	12.5	9.5	2.0	10.0	31.0
Credit rating	15.4	2.2	12.0	15.0	22.0
Crowdedness ($Bn)	3.3	3.8	0.0	2.1	17.4
Order book ($Bn)	3.0	2.2	0.5	2.4	11.1
Issuance premium (bps)	5.5	7.8	-9.3	4.2	35.2
Money Left (MM)	6.1	16.5	-10.3	2.1	79.5
Pct sold first week	0.20	0.15	0.01	0.17	1.00
Issuance credit spread range (bps)	15	14	0	15	61

Source: Mergent FISD, IGM, CFR, eMaxx, TRACE, Markit

Table 9: Broker-dealers as underwriter and issuer versus as underwriter

Broker-dealer	# self-uw bonds	# other bonds	Oversub(self)	Oversub (other)	Issuance range/spread (self)	Issuance range/spread (other)
'CITICORP'	101	46	2.01	2.13	0.11	0.15
'JPM'	95	5	1.84	2.42	0.22	0.13
'BOA'	84	20	2.30	3.39	0.07	-0.13
'GS'	79	18	2.45	2.58	0.09	0.14
'WFC'	67	10	1.81	2.00	0.13	0.11
'HSBC'	58	7	2.46	2.06	0.08	0.16
'MS'	46	17	2.28	3.67	0.04	0.13
'UBS'	33	15	1.96	2.07	0.11	0.13
'DB'	32	13	1.85	2.49	0.10	0.15
'BARC'	29	8	2.29	2.70	0.07	0.13
'CREDSUISSE'	28	6	2.16	2.63	-0.31	0.11
'BNPP'	27	4	2.43	3.22	0.10	-0.23
'RBS'	7	3	1.96	3.00	0.00	0.02
t-test for diff in means, p-value:				0.00294677		0.77707

Notes: Reports for all broker-dealers that underwrite bonds for themselves, the average oversubscription and range of credit spreads for both self-led bond issuances and comparable underwritten bonds issued by other financial firms. To be included in the analysis, bonds issued by other financial firms must be within 2.5 years of bank u's average tenor and within 250MM of bank u's average bond size, rated within 1 notch of bank u's most recent highest rating, and have ≤ 5 underwriters. P-values for two-sample related t-test of difference in means between self-led and comparable bond issuances are reported for both oversubscription and the ratio of issuance credit spread range to final credit spread.

Table 10: Countercyclicality of issuance premiums as % of credit spreads

	(1) Baseline	(2) Issuer controls	(3) UW FE	(4) UW Info
Economic activity	-0.00108***	-0.00108***	-0.00112***	-0.00124***
	(0.000228)	(0.000228)	(0.000234)	(0.000163)
Issuance range / spread			0.125***	0.127***
			(0.0123)	(0.0119)
Credit Rating (log)	0.0122***	0.0122***	-0.00599**	-0.0105*
	(0.00245)	(0.00245)	(0.00294)	(0.00544)
Bond size(log)	0.00338***	0.00338***	0.00182***	0.000392
	(0.000971)	(0.000971)	(0.000517)	(0.00123)
Tenor (years)	-0.00118***	-0.00118***	-0.000883***	-0.000843***
	(0.0000538)	(0.0000538)	(0.0000458)	(0.0000404)
Debt / assets	-0.0245***	-0.0245***	-0.0269***	-0.0663***
	(0.00456)	(0.00456)	(0.00308)	(0.0117)
Cash / assets	0.00698	0.00698	0.00113	0.0107
	(0.00669)	(0.00669)	(0.00553)	(0.00707)
Operating profit / assets	0.354***	0.354***	0.233***	0.297***
	(0.0967)	(0.0967)	(0.0363)	(0.0421)
Firm FE				✓
Underwriter FE	✓	✓	✓	✓
Observations	17113	17113	17113	17074
R-squared	0.0310	0.0310	0.510	0.611

Notes: Outcome variable is ratio of issuance premium to overall credit spread for the same bond. Economic activity is measured using the CFNAI monthly value, collected from the Chicago Federal Reserve, designed to be mean zero with a standard deviation of one. Observations are at the bond-underwriter level. Standard errors clustered at the underwriter.

Table 11: Issuance premiums higher during GFC and COVID-19

	(1) GFC / COVID Dummies	(2) VIX
COVID period (dummy)	12.24***	
	(0.859)	
GFC period (dummy)	13.11***	
	(0.490)	
VIX		0.316***
		(0.0147)
Credit Rating (log)	-16.17***	-15.07***
	(1.702)	(1.698)
Bond size(log)	1.042***	1.353***
	(0.163)	(0.171)
Tenor (years)	-0.0627***	-0.0628***
	(0.00443)	(0.00468)
Debt / assets	-7.123***	-6.433***
	(1.312)	(1.087)
Cash / assets	13.17***	13.77***
	(1.592)	(1.685)
Operating profit / assets	19.71***	10.46
	(6.947)	(6.731)
Firm FE	✓	✓
Underwriter FE	✓	✓
Observations	17074	17074
R-squared	0.520	0.526

Notes: GFC period is an indicator variable for issuance between September 1, 2008, and June 1, 2009. COVID-19 period is an indicator variable for issuance between March 1, 2020, and April 8, 2020. Standard errors are clustered at the underwriter level.

Table 12: Sample summary statistics: bonds issued last 7 days of quarter

	Full sample: Mean	Full sample: StDev	Last 7 days sample: Mean	Last 7 days sample: StDev
Amount ($MM)	632.72	565.85	605.15	499.83
Tenor (Years)	9.60	8.76	10.52	8.44
Credit rating	14.35	4.34	12.77	3.95
Credit Spread (bps)	263.47	222.06	303.96	242.66
Coupon	4.88%	2.48%	5.76%	2.46%
Probability of Default	0.02	0.02	0.02	0.02
First day spread decrease	7.67	11.58	9.90	14.00
Cash/Assets	0.08	0.10	0.06	0.08
Total Debt (log)	8.52	1.77	7.90	1.47
Assets (log)	9.81	1.80	9.13	1.41
Leverage	0.32	0.20	0.35	0.29
Number of bonds		16075		473
Number of firms		4736		314

Source: Mergent FISD, IGM, CFR, Emaxx, TRACE, Markit
Note: This table compares the full sample of bonds, including all USD non-financial corporate bond issuances from 2000-2020, to the subsample of bonds that are issued within the last seven days of the quarter.

Table 13: Bond holders

	Insurance funds	Mutual funds	Pension funds
Num funds	1222.72	1191.03	128.52
AUM (Bn)	9.24	4.37	1.54
Unique bonds held	184.42	274.85	128.96
Unique classes held	52.21	63.89	41.76
Pct held last qtr	0.90	0.84	0.78
Avg length of holdings (qtrs)	8.16	4.41	4.50
Avg length of holdings (pct of tenor)	0.22	0.12	0.13

Source: Thomson Reuters eMAXX
Note: Includes fund holdings reported in eMAXX, 2002-2019. Values are first averaged across all funds within a fund class for each quarter, and then averaged across quarters. Insurance investors include life, health, property and casualty, and diversified insurance. Mutual funds include annuity and money market funds. Pensions include hospitals, governments, and 401K funds.

Table 14: Persistence in set of corporate bonds held by investors

	1	2	3	4	5	6	7	8	9	10	11
AUM_0	0.93	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AUM_1	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AUM_2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AUM_3	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AUM_4	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AUM_5	0.98	0.99	0.99	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
AUM_6	0.98	0.98	0.99	0.99	0.99	0.99	0.99	1.00	1.00	1.00	1.00
AUM_7	0.98	0.98	0.98	0.98	0.98	0.99	0.99	0.99	0.99	0.99	0.99
AUM_8	0.97	0.98	0.98	0.98	0.98	0.98	0.98	0.98	0.99	0.99	0.99
AUM_9	0.98	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99

Source: Thomson Reuters eMAXX
Note: The table shows the percentage of bond classes held in the current quarter that were also held in the previous 1–11 quarters; it is similar to Table 1 of Koijen and Yogo (2019). Each cell gives the median across time (2000–2017) and across all institutions in a given percentile of assets under management.

Table 15: Summary of secondary market holdings demand estimates

Year	Credit_Spread	Rating	Log_Amount	Years_Remaining	Bid_Ask	Probability_Default	UST
2002	0.0003	0.0054	0.0108	-0.5819	-0.0024	-1.6679	0.2893
	(0.000)	(0.013)	(0.005)	(0.718)	(0.002)	(0.355)	(0.355)
2003	0.0007	-0.0026	-0.0002	0.8168	-0.0034	-3.8330	-0.3939
	(0.000)	(0.023)	(0.005)	(0.638)	(0.007)	(1.651)	(0.320)
2004	0.0008	0.0318	0.0006	0.7083	0.0067	-3.7185	-0.3580
	(0.000)	(0.011)	(0.003)	(0.595)	(0.009)	(0.970)	(0.306)
2005	0.0007	0.0189	0.0002	-0.0332	-0.0063	-3.6565	0.0336
	(0.000)	(0.007)	(0.002)	(0.011)	(0.007)	(1.347)	(0.011)
2006	0.0013	0.0032	-0.0069	-0.0256	0.0206	-9.2777	-0.1221
	(0.000)	(0.025)	(0.008)	(0.009)	(0.011)	(4.585)	(0.079)
2007	0.0007	0.0264	-0.0043	-0.0161	-0.0068	-2.9685	-0.0331
	(0.000)	(0.023)	(0.002)	(0.022)	(0.020)	(0.942)	(0.041)
2008	0.0003	0.1854	0.0119	0.1490	0.0093	-0.7102	-0.1066
	(0.000)	(0.098)	(0.016)	(0.109)	(0.008)	(0.711)	(0.055)
2009	0.0011	0.0465	-0.0065	-0.0097	0.0266	-2.5473	0.0140
	(0.000)	(0.028)	(0.009)	(0.042)	(0.025)	(2.435)	(0.025)
2010	0.0004	0.0338	0.0007	0.0263	-0.0083	-1.8440	-0.0086
	(0.000)	(0.007)	(0.001)	(0.022)	(0.004)	(0.378)	(0.012)
2011	0.0008	0.1316	-0.0101	-0.0185	-0.0046	-2.5315	0.0093
	(0.000)	(0.034)	(0.006)	(0.052)	(0.009)	(0.914)	(0.026)
2012	0.0010	0.2033	0.0000	0.0403	-0.0005	-2.6517	-0.0473
	(0.000)	(0.072)	(0.004)	(0.059)	(0.015)	(0.787)	(0.050)
2013	0.0007	0.0293	0.0062	0.0735	0.0013	-2.1723	-0.0478
	(0.000)	(0.014)	(0.003)	(0.056)	(0.006)	(0.820)	(0.027)
2014	0.0011	0.0358	0.0084	0.1319	-0.0013	-3.5942	-0.1360
	(0.000)	(0.044)	(0.008)	(0.120)	(0.013)	(1.243)	(0.113)
2015	0.0010	0.0872	0.0037	0.2927	-0.0465	-3.2577	-0.2927
	(0.000)	(0.031)	(0.003)	(0.180)	(0.021)	(0.888)	(0.169)
2016	0.0007	0.0453	-0.0001	-0.0416	-0.0202	-2.3593	0.0421
	(0.000)	(0.013)	(0.002)	(0.061)	(0.010)	(1.218)	(0.069)
2017	0.0009	0.0623	0.0045	-0.0847	-0.0389	-2.6305	0.0752
	(0.000)	(0.026)	(0.006)	(0.121)	(0.015)	(0.802)	(0.178)
2018	0.0018	0.1490	-0.0012	-0.1471	-0.1245	-6.5650	0.3966
	(0.000)	(0.041)	(0.007)	(0.041)	(0.108)	(1.953)	(0.178)
2019	0.0009	0.0847	-0.0063	-0.0320	-0.0435	-2.1912	0.0048
	(0.000)	(0.019)	(0.003)	(0.010)	(0.018)	(0.554)	(0.046)

Source: Thomson Reuters eMAXX

Note: Coefficients on characteristics are computed for each investor (FUNDID) in each quarter in which the investor holds at least 20 bonds. Estimates here are computed as the mean across all investor-quarters. Standard errors, in parentheses, are computed from the distribution of estimates for each year. Quarterly sample period is from 2002Q1 to 2019Q4. Coefficient estimates on credit spreads are restricted to be positive.

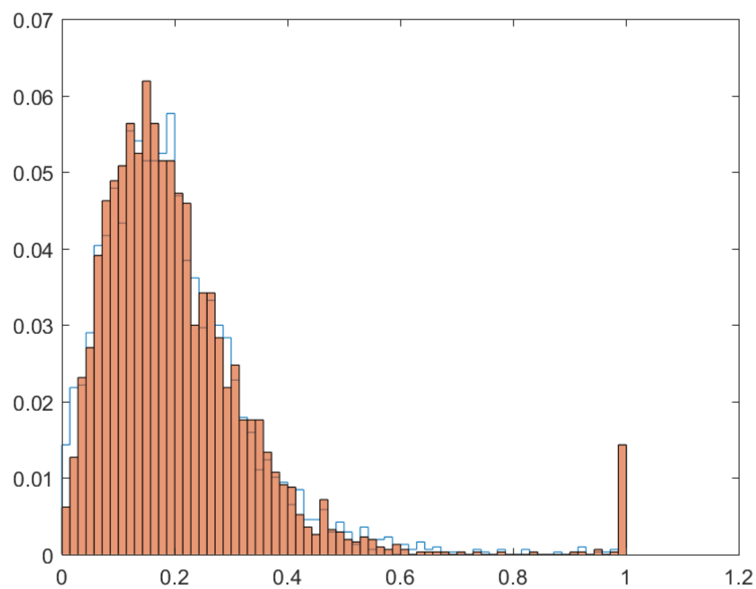
Table 16: Full sample vs. upsized sample of issuers

	Full sample: Mean	Full sample: StDev	Upsized sample: Mean	Upsized sample: StDev
Amount ($MM)	632.72	565.85	614.97	426.92
Tenor (years)	9.60	8.76	9.97	7.46
Credit rating	14.35	4.34	12.00	3.73
Credit spread (bps)	266.63	255.26	318.46	217.56
Coupon	4.88%	2.48%	5.55%	2.13%
Probability of default	0.02	0.02	0.03	0.03
First day spread decrease	6.07	11.60	6.81	12.06
Cash/assets	0.08	0.10	0.06	0.09
Total debt (log)	8.52	1.77	8.12	1.46
Assets (log)	9.81	1.80	9.29	1.41
Leverage	0.32	0.20	0.36	0.22
Number of bonds		16075		2626
Number of firms		4736		1251

Source: Compustat, IGM/CFR, and Mergent FISD.

Notes: Full sample selection includes all USD non-financial corporate bond issuances. Upsized sample includes all bond issuances that are upsized during the day of issuance.

Figure 15: Distribution of short-term share: model fit



Note: I simulate an equilibrium vector of credit spreads, quantities demanded, quantities supplied, and share of short-term investors using the estimated parameters. The shaded region is the actual distribution of the underlying data, from TRACE, and the outline is the model-predicted distribution of the short-term share.

Table 17: Firm supply elasticities (standard tobit)

	(1) All	(2) HY	(3) IG	(4) A-rated	(5) BBB-rated	(6) 2010-2019	(7) 2008-2009	(8) 2020H1
Quantity (log)								
Credit spread (bps)	-0.00221***	-0.00203***	-0.00431***	-0.00579***	-0.00397***	-0.00251***	-0.00152***	-0.00357***
	(0.000223)	(0.000220)	(0.000446)	(0.000520)	(0.000487)	(0.000264)	(0.000583)	(0.000693)
Observations	3433	1744	1689	569	1120	2470	314	125

Note: The table covers sample bonds issued 2000–2020. Observation is by firm-quarter. Dependent variable for all columns is firm-quarter issuance volume, in logs. Standard errors are clustered at the firm level. Standard tobit estimation is left-censored at log of $100 million. I include within-bond fixed effects.

A Additional

A.1 Computing probabilities of default

Using the CDS spreads, I can compute probabilities of default. To do this, I follow Hull (2012) and set the present value of expected CDS payments to the insurer if there is no default (the expression (1) in the following equation) plus the present value of accrued payments made to the insurer in the case of default (the expression (2)) equal to the expected present value of CDS payoffs from the insurer in the case of default (the expression (3)):

$$\underbrace{\sum_{t=1}^{5} s(1-\rho)^t e^{-r_f t}}_{(1)} + \underbrace{\sum_{t=1}^{5} \frac{s}{2}\rho(1-\rho)^{t-1} e^{-r_f (t-\frac{1}{2})}}_{(2)} = \underbrace{\sum_{t=1}^{5} \rho(1-\rho)^{t-1}(1-R) S e^{-r_f (t-\frac{1}{2})}}_{(3)}. \tag{27}$$

I then solve for the implied probability of default based on monthly averages of daily 5-year CDS spreads (s), given a risk-free rate of 3%, a notional amount S, and expected recovery rate R (from the Markit data).

A.2 Computing credit spreads

To compute credit spreads for secondary market holdings, I first compute market yields on all relevant bonds as reported in TRACE data. I primarily rely on the monthly TRACE data reported by WRDS. If this dataset is missing quarter-end yields on bonds, I use Enhanced TRACE data and compute the volume-weighted average of sell-side trades on the last trading day of each quarter. To compute credit spreads, I use the interpolation method described in Gürkaynak et al. (2007). I match the remaining maturity for each bond to the corresponding interpolated risk-free rate. Credit spreads for bond b with remaining term τ at date t are thus

$$cs_{bt}(\tau) = yield_{bt} - r_{ft}(\tau). \tag{28}$$

A.3 Computing yields from TRACE data

Yields reported in TRACE are incomplete and inaccurate. To overcome this, I compute yields directly using the following formula:

$$P = \sum_{t=1}^{T*f} \frac{f}{(1+y/f)^t} + \frac{1}{(1+y/f)^{(T*f)}}, \tag{29}$$

where C is the bond's annual coupon amount, f is the frequency of coupon payments (for example, $f = 2$ for semiannual bonds), y is the yield to maturity, and T is the number of years to maturity of the bond (also known as the tenor). I use a Newton optimization method in Python to compute the yield to maturity y given the rest of the observed bond characteristics and the price P of the bond reported in TRACE.

A.4 Alternative metrics for issuance premium

I employ three alternative methods for computing the first-day returns. A summary table of each metric is below.

1. **Day 1 price return**: I follow Cai et al. (2007) and take the trade-volume-weighted average of prices on all sell trades up to one day following issuance, compute the return relative to the offering price, and then subtract the one-day return on the Bloomberg Aggregate Bond Index.

2. **New issue concession**: This is an ex-ante measure collected by IGM/CFR based on a survey of underwriting banks. This metric is the basis point difference between the yield on a newly issued bond and the market yield on a comparable existing bond.

3. **Issuance premium for first 3 (7) days**: I first compute the yield to maturity on all trades in the first day following issuance, based on TRACE-reported prices. Then I take the trade-volume-weighted average of the yields and subtract the duration-matched U.S. Treasury yield for the first 3 (7) days after issuance to compute the corresponding credit spread. Finally I subtract this computed credit spread from the new issuance credit spread.

Table 18: Alternative metrics for issuance premium

	Mean	Std Dev	Pct 1	Pct 25	Median	Pct 75	Pct 99
Issuance premium (1 day)	7.7	11.6	-9.3	1.4	4.9	9.9	62.4
Issuance premium (3 days)	7.5	17.7	-20.0	1.5	4.9	10.0	65.8
Issuance premium (7 days)	8.1	18.7	-22.7	1.6	5.4	11.0	70.6
New issue concession	4.6	15.9	-30.0	-2.5	3.0	9.0	63.1
CHW Day 1 excess return (based on price)	51.8	80.6	-94.0	4.9	35.2	80.1	352.4
Bloomberg Agg 1 day return (based on price)	-1.1	22.9	-55.0	-14.5	-2.1	12.2	56.9
Bid-ask spread (based on price)	36.2	36.7	2.0	17.0	28.0	44.0	161.0

Notes: This table reports the distribution of the issuance premium used in the baseline estimation, as well as alternative metrics described in Section A.4. Because the Day 1 excess return computed as per Cai et al. (2007) is based on prices, the measure is of larger magnitude. The Bloomberg Agg is the US Agg Total Return Value Unhedged USD Index, pulled from Bloomberg. This index was previously known as the Lehman U.S. Aggregate Bond Index.

A.5 Secondary market demand estimation

I adapt the characteristics-based demand derived in Koijen and Yogo (2019) for equities to corporate bonds. Demand for individual bond b by investor i at time t can then be written as

$$\frac{w_{itb}^{SM}}{w_{it0}^{SM}} = exp\{\alpha_i r_{bt} + \beta_i X_{bt} + \epsilon_{itb}^{SM}\}, \tag{30}$$

which I can rewrite for strictly positive holdings as

$$q_{itb} = q_{it0} + \alpha_i r_{bt} + \beta_i X_{bt} + \epsilon_{itb}^{PM}, \tag{31}$$

where $q_{itb} = \ln(A_{it} w_{itb})$ is the volume that investor i invests in bond b, and $q_{it0} = \ln(A_{it} w_{it0})$ is the volume invested in the outside option of investor i. Characteristics in X include ratings category (log), amount issued (log), remaining years of bond (log), probability of default of the issuer (as derived from its CDS trading), and bid–ask spreads as reported by WRDS. The term ϵ_{itb} is investor i's latent demand; it captures each investor's demand for unobserved characteristics of asset b. Investors choose optimal portfolio weights based on asset characteristics. This equation is essentially a nonlinear regression model of the cross-section in asset demand on asset characteristics. The coefficient α captures investor preference for higher interest rates, or the well-documented tendency to "reach for yield" (Becker and Ivashina (2015)), and is thus restricted to be positive in the estimation.

In classic asset pricing models, investors are atomistic, so demand shocks will not impact prices significantly. Consequently, prices are considered exogenous, and the moment equation $E[\epsilon_{bit}|r_{bt}, X_{bt}] = 1$ can be used for estimation. However, in bond markets, I observe that as investors are large and concentrated, this assumption no longer holds. I therefore need an instrument for the interest rate (price of bonds).

I first make the assumption that (1) wealth distribution across other investors and (2) investment mandates of other investors are exogenous to demand shocks impacting investor i. To justify this assumption, I show empirically that bond investors tend to purchase the same kind of bond. I categorize bonds into categories based on three characteristics: tenor, rating, and industry (two-digit NAIC code). (See Table 14, inspired by Table 1 in Koijen and Yogo (2019).) Using eMAXX data, I first compute the percentage of a fund's reported holdings that is invested in securities that the same fund held in the past 1–11 quarters. Each cell of the table reports the median across percent holdings across funds in the corresponding size class. Investors across the spectrum of sizes (as measured by assets under management) tend to purchase securities of the same class that they have purchased in the past. Investment mandates are plausibly orthogonal to individual bond characteristics, as they appear to change little over time. Thus, I construct the following instrument (with time subscripts suppressed):

$$z_i(b) = \ln\left(\sum_{j\neq i} A_j \frac{\mathbf{1}_j(n)}{1+\sum_{m=1}^{N}\mathbf{1}_j(m)}\right). \tag{32}$$

I define n as the class of bond b. The idea is that, for a given bond b, the more investors there are that have bonds like b in their investment universe, the greater the portion of latent demand for the bond. Moreover, the larger those investors (and the fewer other kinds of bonds they hold), the greater the portion of latent demand. Note that while I estimate this metric for each quarter, the primary source of variation is cross-sectional, allowing me to compute quarterly estimates of all parameters.

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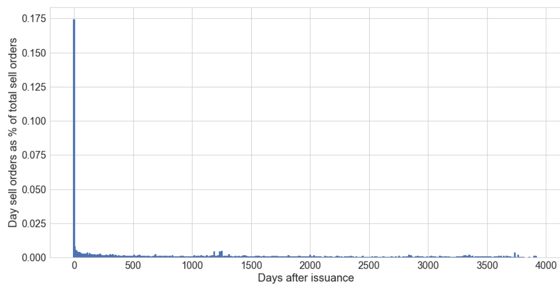
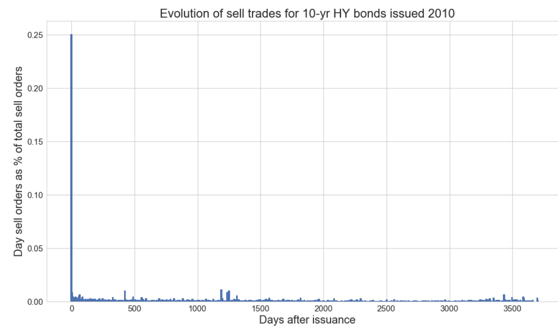
Internet Appendix

A.6 Additional Figures and Tables

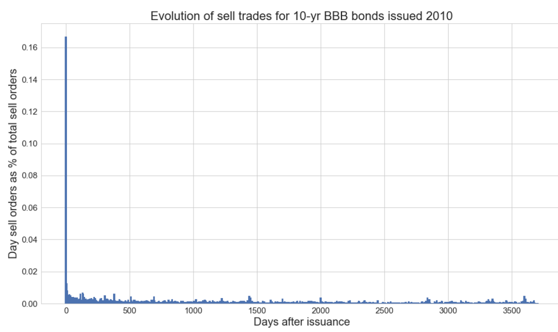
Figure IA.1: Evidence from TRACE: heterogeneous bond buyers



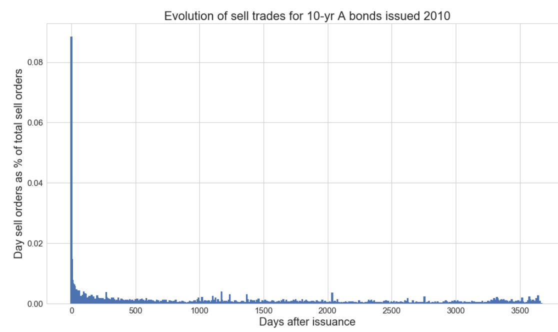
(a) All 10-year bonds issued 2010



(b) HY 10-year bonds issued 2010



(c) BBB-rated 10-year bonds issued 2010



(d) A-rated 10-year bonds issued 2010

Source: Enhanced TRACE
Note: The figure reports the total volume of sell trades in event time since issuance. It includes only USD non-financial corporate bonds issued in 2010 with initial tenor of 9–11 years. The y-axis shows the average across all bonds of share of each day's sell orders as a percentage of total volume of sell orders over the life of the bond (defined as trades between 0 and 4000 days following issuance). The terms "HY bonds", "BBB-rated bonds", and "A-rated bonds" refer to bonds rated below BBB-, between BBB- and BBB+, and A- or higher, respectively.

Table IA.1: Credit rating legend

Moody's	**S&P**	**Fitch**	**Numerical**
Aaa	AAA	AAA	22
Aa1	AA+	AA+	21
Aa2	AA	AA	20
Aa3	AA-	AA-	19
A1	A+	A+	18
A2	A	A	17
A3	A-	A-	16
Baa1	BBB+	BBB+	15
Baa2	BBB	BBB	14
Baa3	BBB-	BBB-	13
Ba1	BB+	BB+	12
Ba2	BB	BB	11
Ba3	BB-	BB-	10
B1	B+	B+	9
B2	B	B	8
B3	B-	B-	7
Caa1	CCC+	CCC+	6
Caa2	CCC	CCC	5
Caa3	CCC-	CCC-	4
Ca	CC	CC	3
C	C	C	2
D	D	D	1

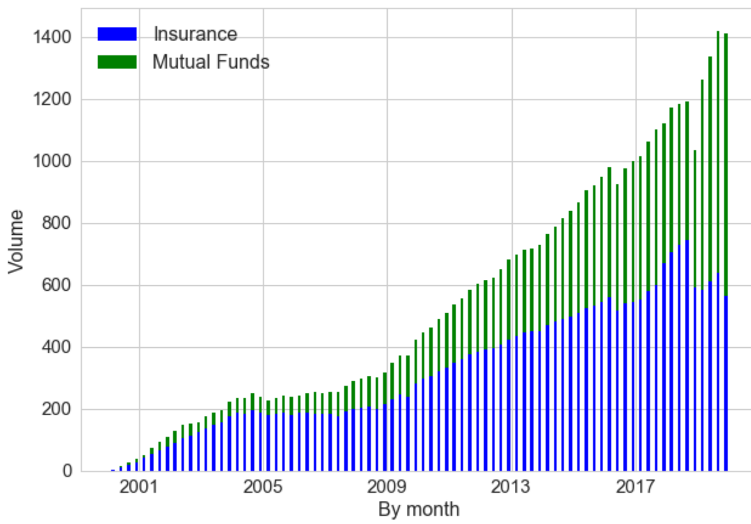


Figure IA.2: Share of insurance versus mutual fund holders of corporate bonds

Source: Thomson Reuters eMAXX
Note: The figure shows the quarterly volume of mutual funds and insurance companies reported to hold corporate bonds in the sample.

B Proofs

Proof of equation (24)*: outside option for investors participating in PM.* Investors take quantity supplied of bonds as given. Thus, their outside option is to purchase the corporate bond at a competitive price in the secondary market, where the quantity demanded equals the amount of the bond issued:

$$Q^{D,PM}(r_b^*) = Q^S. \tag{33}$$

The expression for $q^D(r^*) = \ln\big(Q^D * (r^*)\big)$ is derived as below. Note that I model an expectation of rationing ω, allowing for the possibility that investors anticipate underwriter rationing and scale up their orders accordingly. The baseline model assumes $\omega = 0$, which does not impact the estimation results significantly.

I start with aggregate demand:

$$Q_{bt}^D = W_t\theta_t \frac{\exp\left(\delta_{ST,b}\right)}{\exp\left(\frac{\sigma_t^2}{2k_{ST}}\right) + \sum_m \exp(\delta_{ST,m})} \frac{1}{1-\omega_{ST}} + W_t(1-\theta_t) \frac{\exp\left(\delta_{LT,b}\right)}{\exp\left(\frac{\sigma^2}{2k_{LT}}\right) + \sum_m \exp(\delta_{LT,m})} \frac{1}{1-\omega_{LT}}. \tag{34}$$

For ease of exposition, I make the following substitutions:

$$d_1 = \exp\left(\frac{\sigma^2}{2k_{ST}}\right) + \sum_m \exp(\delta_{ST,m}), \tag{35}$$

$$d_2 = \exp\left(\frac{\sigma^2}{2k_{LT}}\right) + \sum_m \exp(\delta_{LT,m}). \tag{36}$$

For the baseline model, I assume $\omega_1 = \omega_2 = \omega$. Taking logarithms, I get

$$\begin{aligned}
q_{bt}^D &= \ln\big(Q_{bt}^D\big) \\
&= \ln(W_t) - \ln(1-\omega) + \ln\Big[\frac{\theta\exp(\delta_{1b})}{d_1} + \frac{(1-\theta)\exp(\delta_{2b})}{d_2}\Big] \\
&= \ln(W_t) + \omega + \ln\Big[\exp(\delta_{2b})\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\Big] \\
&= \ln(W_t) + \omega + \delta_{2b} + \ln\Big[\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\Big] \\
&= \ln(W_t) + \omega + \theta\delta_{1b} + (1-\theta)\delta_{2b} - \theta\ln(d_1) - (1-\theta)\ln(d_2).
\end{aligned} \tag{37}$$

For the third line, within the second term, I can factor out $\exp\left(\delta_{2b}\right)$. In the second-to-last-line, I make a first-order Taylor approximation around $\theta = 0$:

$$
\begin{aligned}
f(\theta) &= \ln\Big[\frac{\theta\exp(\delta_{1b}-\delta_{2b})}{d_1} + \frac{(1-\theta)}{d_2}\Big] \\
&\approx f(0) + f'(\theta)\Big|_{\theta=0} \times \theta \\
&= -\ln\big(d_2\big) + d_2\Big(\frac{\exp(\delta_{1b}-\delta_{2b})}{d_1} - \frac{1}{d_2}\Big)\theta \\
&\approx -\ln\big(d_2\big) + \Big(\frac{d_2}{d_1}\exp(\delta_{1b}-\delta_{2b}) - 1\Big)\theta \\
&= -\ln\big(d_2\big) + \Big(\exp\big(\delta_{1b}-\delta_{2b}+\ln\Big(\frac{d_2}{d_1}\Big)\big) - 1\Big)\theta \\
&\approx -\ln\big(d_2\big) + \Big(\delta_{1b}-\delta_{2b}+\ln\Big(\frac{d_2}{d_1}\Big)\Big)\theta.
\end{aligned} \tag{38}
$$

I then have

$$
\begin{aligned}
q_{bt}^D = w_t &+ (r_b - r^{SM})\big(\alpha_1\theta_t + \alpha_2(1-\theta_t)\big) + r^{SM}\big(\alpha_{1,SM}\theta_t + \alpha_{2,SM}(1-\theta_t)\big) \\
&+ X_b\big(\beta_1\theta_t + \beta_2(1-\theta_t)\big) + \xi_b + \omega \\
&+ (\theta-1)\ln\big(\exp\big(-k_2/\sigma^2\big) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\big) \\
&- \theta\ln\big(\exp\big(-k_1/\sigma^2\big) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\big).
\end{aligned} \tag{39}
$$

I substitute this last expression into (33) to get

$$
\begin{aligned}
r_b^* = \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}\Big(&q^S - w_t - \omega \\
&+ r^{SM}\big((\alpha_1 - \alpha_{1,SM})\theta_t + (\alpha_2 - \alpha_{2,SM})(1-\theta_t)\big) \\
&- X_b\big(\beta_1\theta_t + \beta_2(1-\theta_t)\big) - \xi_b \\
&+ (1-\theta)\ln\big(\exp\big(-k_2/\sigma^2\big) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\big) \\
&+ \theta\ln\big(\exp\big(-k_1/\sigma^2\big) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\big)\Big).
\end{aligned} \tag{40}
$$

I use the first-stage estimates to compute the implied values for ξ_b, the unobserved common component of investor demand for bond b:

$$
\begin{aligned}
\xi_b = q^D &- w_t - \omega \\
&- (r_b^o - r^{SM})(\alpha_1\theta + \alpha_2(1-\theta)) - r^{SM}(\alpha_{1,SM}\theta + \alpha_{2,SM}(1-\theta)) \\
&- X_b\big(\beta_1\theta_t + \beta_2(1-\theta_t)\big) \\
&+ (1-\theta)\ln\big(\exp\big(-k_2/\sigma^2\big) + \sum_m \exp(\alpha_2 r_m + \beta_2 X_m + \xi_m)\big) \\
&+ \theta\ln\big(\exp\big(-k_1/\sigma^2\big) + \sum_m \exp(\alpha_1 r_m + \beta_1 X_m + \xi_m)\big).
\end{aligned}
\tag{41}
$$

I can then rewrite r^* as

$$
\begin{aligned}
r_b^* &= \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}\Big(q^S - q^D + r_b^o(\alpha_1\theta + \alpha_2(1-\theta))\Big) \\
&= \frac{1}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}\Big(q^S - q^D\Big) + r_b^o.
\end{aligned}
\tag{42}
$$

Rearranging, I have a straightforward way to relate observed credit spreads (r_b^o) to the counterfactual credit spread r^* that would result if investors took q^S (the log bond size) as given, and the bond were priced competitively among investors:

$$
r_b^o - r_b^* = \frac{q^D - q^S}{\alpha_1\theta_t + \alpha_2(1-\theta_t)}. \tag{43}
$$

The issuance premium is a function of the oversubscription (logged), divided by the weighted average demand elasticity of investors.

□

Derivation of aggregate demand Q_{bt} in equation (20). Using properties of the lognormal distribution, I rewrite the investor's objective function as

$$
\max_b - \exp\big(-\frac{1}{k_i}\mu_{ihb} + \frac{\sigma^2}{2k_h^2}\big) \tag{44}
$$

where

$$
\mu_{ihb} = \alpha_h r_b^{PM} + \alpha_{h,SM} r_b^{SM} + \gamma X_b + \xi_b + \epsilon_{ib},
$$

or

$$\max_b - \exp\big(-\frac{1}{k_i}U_i(b)\Big) \tag{45}$$

where

$$U_i(b) = \delta_{hb} + \epsilon_{ib} - \frac{\sigma^2}{2k_h}. \tag{46}$$

Each investor dollar is allocated to the bond that provides the greatest utility:

$$U_i(b) > U_i(m) \qquad \forall m \neq b, \tag{47}$$

where m is the index of all other bonds being issued on the same day.

I now derive the unconditional probability that investor i chooses bond b as per Train (2009). First, I write down the conditional probability that investor i chooses bond b:

$$\begin{aligned} P(i \text{ choose } b) &= P(U_{ib} > U_{im} \ \forall m \neq b) \\ &= P(\delta_{hb} + \epsilon_{ib} - \frac{\sigma^2}{2k_h} > \delta_{hm} + \epsilon_{im} - \frac{\sigma^2}{2k_h} \ \ \forall m \neq b) \\ &= P(\epsilon_{im} < \delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib} \ \ \forall m \neq b). \end{aligned} \tag{48}$$

Suppose first that ϵ_{ib} is known. Since the ϵ terms are independent, the probability of investor i choosing b is just the cumulative distribution function (CDF) for each potential value of ϵ_{im} for all $m \neq b$, and I can write the CDF for all bonds $m \neq b$ as the product of the CDFs for the individual bonds:

$$P(i \text{ choose } b|\epsilon_{ib}) = \prod_{m \neq b} \exp\big(-\exp\Big(-(\delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib})\Big)\big). \tag{49}$$

Since I do not observe any of the ϵ_{ib} values in reality, I evaluate the unconditional probability that investor i chooses bond b by integrating over all potential values of ϵ_{ib}. I assume the outside option has $U_{0h} = 0$ for every h. I then obtain the following expression for the probability that investor i

chooses bond b out of a given market t:

$$\begin{aligned} P_{ib} = P(i \text{ choose } b) &= \int \prod_{m \neq b} \exp\Big(- \exp\Big(-(\delta_{hb} - \delta_{hm} + \frac{\sigma^2}{2k_h} - \frac{\sigma^2}{2k_h} + \epsilon_{ib}) \Big) \Big) f(\epsilon_{ib}) d\epsilon_{ib} \\ &= \frac{\exp\big(\delta_{hb} - \frac{\sigma^2}{2k_h}\big)}{1 + \sum_m \exp\Big(\delta_{hm} - \frac{\sigma^2}{2k_h}\Big)} \\ &= \frac{\exp\big(\delta_{hb}\big)}{\exp\Big(\frac{\sigma^2}{2k_h}\Big) + \sum_m \exp(\delta_{hm})}. \end{aligned} \tag{50}$$

Next, I need to map the probability of investor i participating in the primary market for bond b to the total quantity demanded for bond b as observed in the data. The aggregate demand for bond b in market t is just the sum over all types of investors that unconditionally choose to purchase bond b:

$$Q^D_{bt} = \sum_h P_{hbt} M_{ht}. \tag{51}$$

Assume there are only two types of investors: a proportion θ_t that are short-term investors, and a proportion $(1-\theta_t)$ that are not. Market size M_{ht} is defined as the proportion of type h in the full amount of investor wealth in market t: $M_{ST,t} = W_t \theta_t$ and $M_{LT,t} = W_t(1-\theta_t)$, where W_t is the whole universe of potential investors in a given market t. Note that $w_t = \ln(W_t)$. The aggregate demand is then given by

$$Q^D_{bt} = W_t \theta_t \frac{\exp\big(\delta_{ST,b}\big)}{\exp\Big(\frac{\sigma^2}{2k_{ST}}\Big) + \sum_m \exp(\delta_{ST,m})} + W_t(1-\theta_t) \frac{\exp\big(\delta_{LT,b}\big)}{\exp\Big(\frac{\sigma^2}{2k_{LT}}\Big) + \sum_m \exp(\delta_{LT,m})}. \tag{52}$$

□

Derivation of firm's supply of bond in equation (6). Note that given the normal error, I can write the unconditional expectation of issuance q for a given firm as

$$\begin{aligned} E[q|Z] &= Pr(q > 0|Z) \times E[q|Z, q > 0] \\ &= \Phi((\gamma_r r + Z\gamma - c)/\sigma_e) \times E[q|Z, q > 0], \end{aligned} \tag{53}$$

where, following the standard censored tobit model (see Wooldridge (2002), Chapter 16),

$$E[q|Z,q>0] = \gamma_r r + Z\gamma + E[u|u > c - \gamma_r r - Z\gamma] = \gamma_r r + Z\gamma + \sigma_e\Big[\frac{\phi((\gamma_r r + Z\gamma - c)/\sigma_e)}{\Phi((\gamma_r r + Z\gamma - c)/\sigma_e)}\Big]. \quad (54)$$

Note further that the change in expected issuance, unconditionally, given a change in r, is

$$\frac{\partial E[q|Z,r]}{\partial r} = \gamma_r \Phi\big((\gamma_r r + Z\gamma - c)/\sigma_e\big), \quad (55)$$

where $\Phi\big((\hat{\gamma}_r r + Z\hat{\gamma} - c)/\hat{\sigma}_e\big) = Pr(q > 0|Z,r)$ is the estimated probability of issuing given Z, r.

□